Study on Adaptation Modelling

Comprehensive Desk Review: Climate Adaptation Models and Tools

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Introduction

This document provides a comprehensive desk review of climate adaptation models and tools for the "*Study on Adaptation Modelling*" on behalf of the Directorate General for Climate Action (DG CLIMA) (CLIMA/A.3/ETU/2018/0010). This work was undertaken by a consortium led by Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC) and includes Deltares, the Institute for Environmental Studies (IVM) and Paul Watkiss Associates (PWA).

Aim of the study

This comprehensive desk review aims to address the European Commissions' requirement to support better-informed decision making on climate adaptation at multiple governance levels: it provides a comprehensive, up-to-date and forward looking overview of the range of technical, financial, economic and non-monetary models and tools for hazards, risks, impacts, vulnerability and adaptation climate assessments. This therefore aims not only to collate current knowledge on climate adaptation assessment methodologies, but to highlight research gaps in each field. This review subsequently informs a recommended approach for adaptation modelling, detailed in further reports.

Structure of the comprehensive desk review

The comprehensive desk review constitutes a report overviewing the key groups of model and tool methodologies, which provides a reference guide to the supporting annex detailing greater specific use of individual models and tools.

In order to support policy decision-making, the review considered the requirement for assessment tools and methodologies to support each stage of the adaptation policy cycle[1] (figure 1).

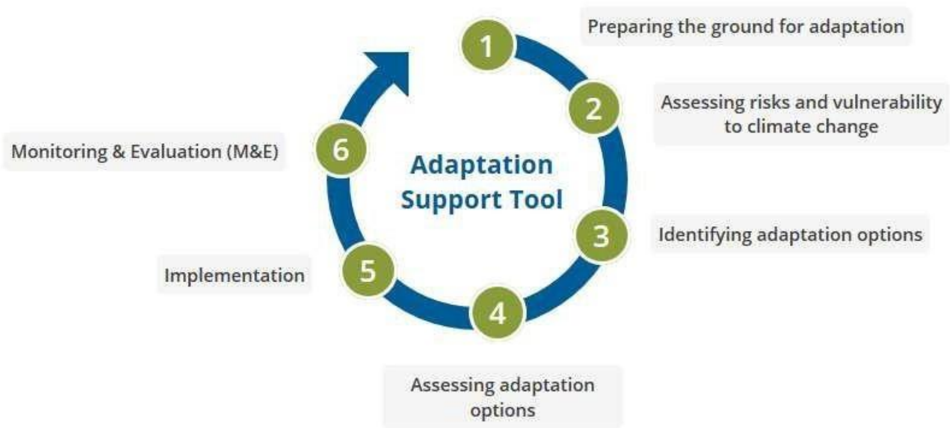

Figure 1: Climate-ADAPT Adaptation Policy Cycle (European Environment Agency).

[1] https://climateadapt.eea.europa.eu/knowledge/tools/adaptation-support-tool

As such, the consortium developed an adaptation modelling typology to reflect this, as well as the range of models and tools for both environmental and socio-economic assessments (figure 2).

Climate system → Env. system → Social-Ec. system

Models

Climate modelling (for adaptation)	Hazard, exposure and vulnerability modelling	Sectoral models for impact and adaptation assessment	Economic models for impacts and adaptation assessment	Other techniques	How to use the information (principles and methods)
Climate models which provide inputs for risk, impact and adaptation assessments.	Models and techniques which utilise climate variables to develop climate risk assessments. These provide inputs further processed by impact models, such as crop and energy models, detailed under 'sectoral models for impact and adaptation assessment'.	These models process 'hazard, exposure and vulnerability modelling' outputs to quantify the impact of climate change on sectors that provide essential services to society, the environment and the economy. These can support identifying adaptation options.	Top-down macro-economic models inform the choice of adaptation measures, or mix of measures and policies, often under substantial and non-reducible, deep uncertainty. Other economic assessments test strategies to support the uptake of adaptation measures.	Further analysis, using qualitative or semi-qualitative techniques, that can support adaptation assessments.	Scrutiny of analytical "conceptual frameworks" and of methodologies that substantiate them in adaptation analyses.

Figure 2: Climate adaptation modelling typology.

Due to the emphasis of developing understanding regarding climate *adaptation* assessments and methodologies, climate modelling, the first column of the typology, has been excluded from this compendium. A compilation of climate tools to access climate data has been compiled by Copernicus' Climate Data Store and toolbox.[2]

Therefore, the comprehensive desk review is structured according to the remaining model categories:

1. Hazard, exposure and vulnerability modelling
2. Sectoral models for impact and adaptation assessment
3. Economic models for impact and adaptation assessment
4. Other techniques
5. How to use the information (principals and methods)
6. Future research

1. Hazard, exposure and vulnerability modelling

When developing climate adaptation measures, the aim is to address one or more components of risk (UNDRR, 2016)[3] which is commonly defined as the product of hazard, exposure and vulnerability. Climate hazards constitute agents of disaster based on their impact on humans and the environment (Hobbs, 1987) and models typically utilise weather and climate data as inputs as, for example, can be found at the Copernicus Climate Data Store. Exposure refers to the elements located within the area of a hazard occurrence, while vulnerability describes the propensity of these elements, such as people, livelihoods and the environment, to the impacts of these hazard events (Cardona *et al.*, 2012). Therefore, the first chapter examines hazard, exposure and vulnerability modelling to support the establishment of climate risks to be addressed within climate adaptation strategies. The identification of extreme climate events, changes in their spatial and temporal occurrence, and the

[2] https://climate.copernicus.eu/what-we-do

[3] UNDRR (2016). Report of the open-ended intergovernmental expert working group on indicators and terminology relating to disaster risk reduction. Retrieved from http://www.preventionweb.net/drr-framework/open-ended-working-group/

compounding impact of multiple hazards are also paramount in identifying risk (de Ruiter *et al.*, 2020), and therefore methods to examine these factors are also included in this chapter.

2. Sectoral models for impact and adaptation assessment

Climate hazards can impact multiple sectors that provide essential services to society, the environment and the economy. Modelling the impact and response of these sectors to climate events, such as the impact of flooding on urban areas, supports the tailoring of adaptation strategies to reduce the resulting negative consequences. The model groups detailed in this section typically use outputs from the previous chapter on hazards, their extremes, exposure and vulnerability as inputs. Examples of these sectors include, but are not limited to, tourism, agriculture, and ecosystems and biodiversity.

3. Economic models for impact and adaptation assessment

An assessment of the efficiency of adaptation measures requires an understanding of economic models. Macro-economic models, including integrated assessment models (IAMs) and computed general equilibrium models (CGEs), provide top-down, economic-oriented models to inform the choice of adaptation measures or mix of measures and policies, often under substantial and non-reducible, deep uncertainty. Other economic assessments include insurance impact assessments and behavioural economic experiments, which are important for assessing smaller-scale economic strategies to promote the uptake of adaptation measures.

4. Other techniques

Under a range of different settings in which climate adaptation decisions are required, further analysis may be necessary to provide a holistic assessment that further inform impact assessments detailed in chapter 2. This chapter presents qualitative and semi-qualitative techniques of agent-based models, stakeholder and multi-criteria analyses where the interests of multiple stakeholders need to be considered.

5. How to use the information (principals and methods)

This chapter presents methods which can use information from the previous four chapters to support decision making based on different requirements and situations, for example, when decision makers are operating under high degrees of future uncertainty or comparing the effectiveness of different identified adaptation strategies.

6. Future research

A sixth and final chapter "Future research" has been included which appraises the literature within this comprehensive desk review, conducting a gap analysis to provide recommendations for future research.

Typical questions that can be addressed using the model groups described within this desk review are highlighted in figure 3. Here, answering initial questions such as which hazards are present, whether there are multiple and compounding events, what is the severity and frequency, who is vulnerable and where is exposed, can inform questions regarding which sector(s) are impacted and what adaptation measures could reduce this impact. A sector-specific user should also start with hazard, exposure and vulnerability modelling before applying sector-specific models and tools. Subsequently, wider economic analysis, in conjunction with any further analyses (if applicable) and use of decision support systems can develop on sector impact modelling to inform holistic climate adaptation strategies. Table 1 highlights which chapters of this review may be relevance to identified key end users operating at the European, national and local or project spatial scales. These key end users include policy and public decision makers; investment, finance and insurance; business and industry (private sector); research and civil society and NGOs.

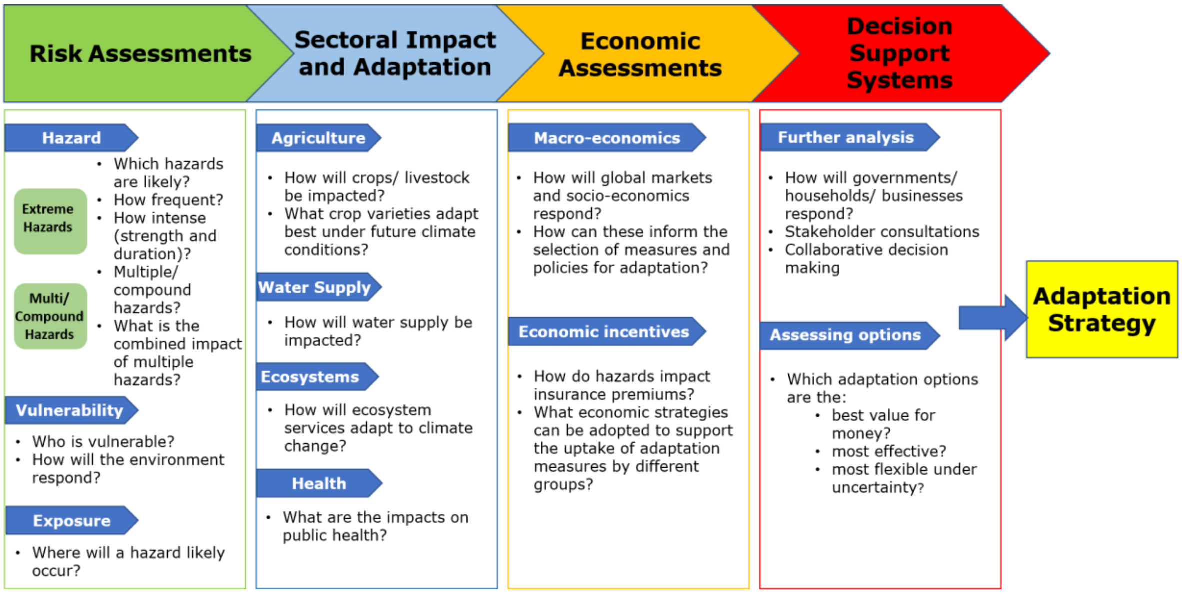

Figure 3: Key example questions that can be examined and used to support the development of climate adaptation strategies.

It should be noted that multiple hazards can impact multiple sectors and, as such, table 2 highlights some of the overlaps in topics between chapters 1 and 2 which may be relevant to consider. Given that economic models (chapter 3), other techniques (chapter 4) and decision support systems (chapter 5) are not hazard or sector-specific, with the exception of chapter 5.7 'Urban adaptation tools and models', these have not been included in table 2. Therefore, it may be useful for users to consider these other chapters, dependent on the individual case or project.

What specific information does this review present?

The discussion within each chapter, which provides an overview of the key groups of model and tool methodologies, follows a set template:

1. An initial short overview is provided to guide the reader on the aims of the model groups described.
2. Each chapter identifies the main users or applications and their scale: local/project, national, European. These users include the following: policy and decision makers; investment, finance, and insurance sector; private sector; research; and civil society and NGOs. However, it should be noted that while there are some groups of models that operate at a specific spatial scale, such

as urban models, generally the scale of the analysis is often highly dependent on the scale of the available input data.

3. The step(s) of the adaptation policy cycle (as shown in figure 1) which can be supported by the model groups are identified, along with the general model outputs and how they can support adaptation policy or decision making. This supports the user to identify the applicability of the model groups for their specific case or project.
4. A short technical summary of the key modelling methodologies, their assumptions and methods to test the quality of the models are provided. This provides more in-depth information regarding the model groups and some examples of specific models within these groups. This can support users to identify which model methodologies are most appropriate and guides towards relevant specific models which can be used, as detailed in the annex.
5. The required climate, socio-economic and other input data of importance to the model are outlined.
6. The outputs, in conjunction with examples of how these model groups have been previously applied, are outlined to demonstrate how these model groups have successfully been used. This assists the user in justifying the selection of a model group.
7. The main strengths and weaknesses of the model groups are summarized in a table. This assists the user to identify under which situations the model groups are best applied.
8. To assist in the identification of whether certain groups of models or tools can be used for rapid assessment, a short discussion is provided to highlight whether and how the models can be used in for this.
9. Finally, existing research gaps in terms of data availability, research regarding the use and application of the tool are discussed. A summary of the research gaps across climate adaptation modelling can be found in chapter 6 'Future research'.

Overall, the desk review covers a wide range of topics within the process of developing adaptation strategies, which aims to provide a bridge in understanding between the technicalities of adaptation modelling and decision making. It is hoped that the desk review will represent a guide for users to progress information accessibility beyond academia. Together, not only could the review promote understanding of what is currently possible but guide our future efforts to develop our knowledge further.

Table 1: Chapters of relevance to end users operating at different geographical scales.

		Hazards										Extreme climate				Exp	Vuln.			Sectors			
		Heatwaves	Drought	Forest fires	Land desertification	Heavy precipitation	Windstorms	Hailstorms	Flow and river flow	Landslides & avalanches	Coastal and sea level rise	ETCCDI indices	Extreme value analysis	Spatio-temporal patterns	Multi-risk, compound…	Scenarios	Socio-economic	Ecosystem	Resilience analysis	Water supply	Agriculture/ crops	Forestry	Fish dyn.: *Frequentist stats*
Policy & public decision makers	European	■	■	■		■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	National	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	Local/ Project	■	■	■	■	■	■	■	■	■	■	■		■	■	■	■	■	■		■	■	■
Investment, finance & insurance	European	■				■	■	■	■	■		■	■	■	■	■	■		■	■			
	National	■	■			■	■	■	■	■	■	■	■	■	■	■	■		■	■			
	Local/ Project	■	■			■	■	■	■	■	■	■	■	■		■	■		■				
Business & industry (private sector)	European	■		■		■	■			■	■	■		■		■	■	■	■	■	■		
	National	■		■		■	■			■	■	■		■	■	■	■	■	■	■	■	■	
	Local/ Project	■			■	■	■			■	■	■	■	■		■	■	■	■	■	■	■	
Research	European	■	■	■		■	■		■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	National	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	Local/ Project	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
Civil Society and NGOs	European	■		■		■			■	■		■		■		■	■	■	■	■	■	■	■
	National	■		■	■	■			■	■	■	■		■	■	■	■	■	■	■	■	■	■
	Local/ Project	■	■	■	■	■			■	■	■	■	■	■	■	■	■	■	■		■	■	■

		Sectors (cont.)															
		Bayesian stats	*Classification models*	*Mechanistic models*	*End-to-end*	Ecosystems & biodiversity	Energy	Tourism: *Physical changes*	*Tourism climate index*	*Demand models*	*Inclusion in IAMs*	Cities and urban areas	Critical infrastructure	Buildings	Transport	Health and heat	Health and other
Policy & public decision makers	European	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■
	National	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	Local/ Project	■	■	■	■	■	■	■	■			■	■	■	■	■	■
Investment, finance & insurance	European				■		■			■	■		■	■	■		
	National				■		■	■	■	■	■		■	■	■		
	Local/ Project				■		■	■	■								
Business & industry (private sector)	European	■			■	■	■	■	■	■	■		■		■		
	National	■			■	■	■	■	■	■	■		■	■	■		
	Local/ Project	■			■	■	■	■	■								
Research	European	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	National	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	Local/ Project	■	■	■	■	■		■	■			■		■		■	■
Civil Society and NGOs	European		■		■	■		■					■	■	■		
	National		■		■	■		■					■	■	■		
	Local/ Project		■		■	■		■	■					■			

		Economic Models					Other tech.			How to use the information						
		IAMS	CGEs	Macro-economic models	Behavioural economics	Insurance	Agent-based models &…	Stakeholder analysis	MCA	Cost-benefit analysis	Cost effectiveness	DSS	Real option analysis	Robust decision making…	DAPP	Urban adaptation tools
Policy & public decision makers	European	■	■	■	■	■	■	■	■	■	■	■	■		■	■
	National	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	Local/ Project				■	■	■	■	■	■	■	■	■	■	■	■
Investment, finance & insurance	European			■	■	■	■	■	■	■	■	■	■			
	National			■	■	■	■	■	■	■	■	■	■			
	Local/ Project				■	■	■	■	■	■	■	■	■	■		
Business & industry (private sector)	European							■	■		■	■	■			
	National						■	■	■	■	■	■	■			
	Local/ Project						■	■	■	■	■	■	■			
Research	European	■	■	■	■	■	■	■	■	■	■	■	■		■	■
	National	■	■	■	■	■	■	■	■	■	■	■	■	■		■
	Local/ Project				■	■	■	■	■	■	■	■	■	■		■
Civil Society and NGOs	European							■	■		■	■				
	National							■	■		■	■				
	Local/ Project							■	■		■	■				

Table 2: Models from multiple chapters can inform impact and adaptation analyses in a number of other hazard, exposure, vulnerability and sectoral investigations. Such potential overlaps are highlighted in orange

		Hazards										**E. c. events**				**Exp**	**Vuln.**			**Sectors**												
		Heatwaves	Drought	Forest fires	Land desertification	Heavy precipitation	Windstorms	Hailstorms	Flow and river flow	Landslides and avalanches	Coastal and sea level rise	ETCCDI indices	Extreme value analysis	Spatio-temporal patterns	Multi-risk, compound…	Scenarios	Socio-economic	Ecosystem	Resilience analysis	Water supply	Agriculture/ crops	Forestry	Fish dynamics	Ecosystems & biodiversity	Energy	Tourism	Cities and urban areas	Critical infrastructure	Buildings	Transport	Health and heat	Health and other
Hazards	Heatwaves																															
	Drought																															
	Forest fires																															
	Land desertification																															
	Heavy precipitation																															
	Windstorms																															
	Hailstorms																															
	Flow and river flow																															
	Landslides and avalanches																															
	Coastal and sea level rise																															
Extreme climate events	ETCCDI indices																															
	Extreme value analysis																															
	Spatio-temporal patterns																															
	Multi-risk, compound…																															
Exposure	Scenarios																															
Vulnerability	Socio-economic																															
	Ecosystem																															
	Resilience analysis																															
Sectors	Water supply																															
	Agriculture/ crops																															
	Forestry																															
	Fish dynamics																															
	Ecosystems & biodiversity																															
	Energy																															
	Tourism																															
	Cities and urban areas																															
	Critical infrastructure																															
	Buildings																															
	Transport																															
	Health and heat																															
	Health and other																															

Chapter 1.0: Hazard, exposure and vulnerability modelling

When developing climate adaptation measures, the aim is to address one or more components of risk (UNDRR, 2016)[4] which is commonly defined as the product of hazard, exposure and vulnerability. This first chapter therefore examines hazard, exposure and vulnerability modelling to support the establishment of climate risk to be addressed within climate adaptation strategies. The identification of extreme climate events, changes in their spatial and temporal occurrence, and the compounding impact of multiple hazards are also paramount in identifying risk, and therefore methods to examine these factors are also included in this chapter.

[4] UNDRR (2016). Report of the open-ended intergovernmental expert working group on indicators and terminology relating to disaster risk reduction. Retrieved from http://www.preventionweb.net/drr-framework/open-ended-working-group/

1.1 Hazard modelling

1.1.1 Heatwaves

Increasing global temperatures are expected to affect the frequency and intensity of heat extremes, with consequential impacts on human health, ecosystems, and socio-economic systems. There is no specific definition of heatwave since they are generally identified to highlight the effect of temperature increase on a specific sector of interest (Pasqui and Di Giuseppe, 2019). Based on the indications provided by the Expert Team on Climate Change Detection and Indices working group (ETCCDI) (section 1.2.1), a heatwave can be defined as the occurrence of at least six sequential days with maximum daily temperature, or temperature daily minimum, above the corresponding daily threshold value at the 90th percentile (Karl *et al.*, 1999). Future temperature values are simulated using Global Circulation Models (GCMs) and Regional Climate Models (RCMs), which support the estimation of temperature variation under projected scenarios in relation to a reference period. Evaluating the frequency and severity of temperature extremes is fundamental for the climate adaptation challenge: the use of indices is a common tool for assessing and evaluating the evolution of these characteristics under future climate conditions.

Users and application

End-users of these indices include:

	European	National	Local/Project
Policy and public decision-makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

The assessment of heatwaves pattern changes can support the adaptation policy cycle:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options.

The assessment of historic and future temperature projections supports the evaluation of hazard levels associated with heat extremes and its potential variation. Combined hazard, exposure and vulnerability maps represent a useful tool for advising and supporting policy decisions on adaptation and risk reduction for extreme temperature events. For planning purposes, it is necessary to understand whether future temperature extremes will emulate historical trends or manifest with increasing frequency and/or severity. Furthermore, the early identification of temperature extreme occurrences can support early warning systems and the subsequent response rate. Responsibility for the management of early warning systems can vary in some instances, which may fall under public health agencies or, in other locations, specialised emergency management departments may have been established. (McCormick, 2010b).

Analysis of observational temperature data provides evidence for historical and recent climate trends. Additionally, analysis of climate modelling projections supports the assessment of expected variations in the frequency and intensity of extreme events, and for identifying priority areas, which can justify implementing adaptation strategies in response to risks associated with extreme temperatures.

Model and tool methodology

Heatwave spatial and temporal distribution can be assessed using temperature data modelled by GCMs and RCMs. In particular, RCMs can provide higher spatial resolution climate patterns for temperature and related features for historic and future periods. Future temperature projections are based on the various IPCC scenarios, and heatwave conditions can be predicted by comparing projected climate data in relation to a reference climate period. Subsequently, expected climate anomalies are identified. Changing aspects of temperature pattern trends, such as the magnitude and frequency of heatwaves, can be assessed using specific climate indices and indicators, which operatively support the establishment of the spatial distribution of these intense events and their expecting variations under future climate projections (Silliman et al, 2013a, b). Among the most common indices used for the analysis of the heatwaves, are SU, TR, TX90p, TNx, and WSDI, detailed in section 1.2.1.

A deep review of the methodologies proposed to measure and assess heatwave changes at a global scale is provided in Perkins (2015).

Assumptions

Projections of potential changes in future heatwave patterns and intensity are based on the interaction of large- and small-scale processes generated by GCMs. Such climate models possess varying degrees of uncertainty across different global regions, which has been demonstrated through statistical comparison with observational data (Vaurtard *et al.*, 2013).

Model verification

GCM and RCM results can be verified using comparisons with observational data (Scoccimarro *et al.*, 2017; Russo *et al.*, 2014). Furthermore, reanalysis data sets are also often applied for model evaluation: reanalyses are comparable with model simulations due to their gridded output and similarity of scales represented. Therefore, variables that are directly assimilated in the reanalysis forecast models are typically closer to observations (Silliman *et al.*, 2013a).

Input data

Temperature time series can be derived using in situ and remote sensing observations for an explicit period of time, as well as climate model simulations' reanalysis and projections for both historical and future time periods. In Europe, historic, present and future high-quality climate datasets are provided by the Copernicus Climate Change

Service's Climate Data Store (CDS), a web-platform providing freely available climate data.[5]

Climate projections are usually evaluated using GCMs, which account for different GHGs concentration scenarios such as those provided in the 5th Assessment Report published by the IPCC. GCMs results are, in general, dynamically downscaled by RCMs, which are able to provide a more accurate description of climate variability with a higher spatial resolution (Jacobs *et al.*, 2014).

In order to provide a comprehensive assessment of proposed adaptation strategies, socio-economic data are required in order to assess an area/ population's potential resilience to heatwaves. Such data could include population density, land use and pre-existing blue/green infrastructures.

Outputs

The use of these input data supports the reconstruction of daily air temperature trends (Pasqui and Di Giuseppe, 2019), which can be used to generate indices that can be graphically mapped to identify temperature anomalies and heatwave events. The analysis of historic and future trends in spatial and temporal distribution patterns of heatwaves events can support the assessment of climate change-induced variability.

The ETCCDI indices related to temperature extremes can be useful for defining Heat Warning Systems (SREX, 2012), alert systems, information outreach plans, long-term infrastructural planning, and preparedness actions for health care systems (WHO, 2007) such as Meteoalarm, established by The European Network of Meteorological Services to coordinate and differentiate warnings across regions (Bartzokas *et al.*, 2010). See section 2.12 for more information regarding heat and health systems.

At a global scale, the IPCC (AR5, 2013) highlighted that the frequency and intensity of heatwave events have likely increased and that the maximum daily temperatures are increasing faster than the annual average temperature. Further, projections from the ensemble models of EURO-CORDEX community (Jacob *et al.*, 2014) indicated that extreme meteorological events, including heatwaves, will significantly increase in the future.

An overview of expected changes in extreme weather and climate events across Europe is provided in Hov *et al.* (2013). The study highlights the trends of a number of climate variables observed in recent decades and provides future projections. It also indicates that one of the most significant effects of climate change will be a shift in weather patterns and, subsequently, extreme weather occurrence. While accounting for temperature, the study documents a regional increase in the frequency of heatwaves in, among other locations, Portugal and the Eastern Mediterranean. Specifically, by analysing the available data and projections, the study highlights that the probability of occurrence of heatwaves, such as those in 2003 in Europe or 2010 in Russia, is expected to increase substantially. For example, what is currently a 1 in 50-year event may become a 1 in 5-year event by the end of the 21st century.

[5] https://climate.copernicus.eu/climate-data-store

Furthermore, the study also provided an overview of the suitable adaptation planning to different risks and at different geographic scales.

Strengths and weaknesses

Strengths	Weaknesses
Information on the intensity, severity and duration of temperature extremes are easily used as input data for impact models.	Extreme indices calculations require long-term and high-quality data series.
	Observational data: limited availability of high-resolution spatial and temporal data. Projected/simulated data: uncertainties associated with climate models predominately due to different emission scenarios, model parameterization, and dataset reliability.
	In some EU countries, data records are short and contain poor spatial resolution.

Suitability for rapid assessment

The adoption of an index-based approach for the evaluation of heatwave trend variation can be used as a rapid analysis tool since indices support the assessment of changes in hazard levels without running complex models that require high computational effort and ancillary information for their calibration.

Research gaps

The main gap associated with the assessment of heatwave events and their trends is a lack of long-term data records. Specifically, at European level, many regions either do not have any records or sparse in situ data. A greater number of in situ monitoring stations with long records are available in Germany (EEA, 2017), where more detailed analyses can be carried out and validated. The indicator approach also does not account for indirect factors that can potentially exacerbate the intensity of heatwave events, such as the urban heat island effect and wind intensity.

1.1.2 Drought

To prevent, mitigate and prepare for drought disasters, accurate understanding of drought risk is required. Effective risk reduction requires research into the causes, frequencies and intensities of droughts, as well as the exposure and vulnerability of affected populations and economic sectors (WMO, UNCCD and FAO, 2013). Forecasting and modelling droughts and their impacts has proven to be complex (Deltares 2018a,b). Drought models and techniques utilise climate variables and aim to inform impact assessments. However, "*there is no independent, systematic body of research to show when droughts are likely to occur, for how long, and what their impact is likely to be*" (Nature Editorial, 17/09/2019). The absence of a consensus regarding the definition of drought (Slette *et al.*, 2019) and the diversity of types of drought impacts (Wilhite and Glantz, 1985) in conjunction with data scarcity regarding drought vulnerability (Blauhut, 2015), have resulted in a plethora of varying drought hazard, risk and adaptation calculation methods (Mishra and Singh, 2011). Consequently, models and tools differ in their assessment of sectoral impacts between studies and specific research questions. A comprehensive overview of all the drought hazard and risk models and tools was recently published by the World Bank (World Bank, 2019).[6]

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.		x	x
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.			x

These drought models and tools are able to support the policy cycle at:

- Step 2: Assessing risks and vulnerability to climate change
- Step 4: Assessing adaptation options.

Most current models and tools aim to quantify drought hazard while some also aim to predict drought impacts. Drought vulnerability assessments need to consider "*the conditions determined by physical, social, economic and environmental factors or processes which increase the susceptibility of an individual, a community, assets or systems to the impacts of hazards*" (UNDRR terminology, 2017). However, this can be challenging and therefore qualitative or semi-quantitative methods are usually applied: estimating the impacts of, for example, food insecurity or expected food aid requirements are based on expert assessments and information in the field rather than through systematic modelling. The effect of multiple adaptation options on the overall drought risk can therefore only be quantified in models that include vulnerability and can be used for further assessments such as cost-benefit analysis (CBA) (section 5.1).

[6] www.droughtcatalogue.com

General drought risk models and eco-hydrological monitoring tools can be used to support policy makers to identify areas at high risk to the impacts of drought, while agricultural drought risk models (section 2.2) are used by governments, NGOs and farmers to assess climate-smart farm practices and policies.

Models which include drought vulnerability can estimate the number of people or livestock exposed to droughts and predict when and where a drought will occur. This can be interpreted by, for example, local food security experts, and combined with market prices and food market accessibility information to estimate impact levels. Crop models can additionally quantify the benefit of certain agronomic or agricultural water management adaptation options in relation to reduced yield losses due to droughts. These can drive policy decisions for awareness and prevention measures.

Model and tool methodology

Droughts can arise from a range of hydro-meteorological processes that suppress precipitation and/or limit surface water or groundwater availability, creating conditions that are significantly drier than average or limiting moisture availability to a potentially damaging extent (WMO, 2016). The types of droughts commonly identified are meteorological, hydrological, agricultural, and socio-economic drought (Wilhite and Glantz, 1985). While this first type can only be influenced by climate variability, the other three have significance anthropogenic influences and are also directly linked to potential impacts (Van Loon *et al.*, 2016). Hydrological drought is associated with the effects of precipitation deficit on surface or subsurface water supply. Agricultural drought links various characteristics of meteorological and hydrological droughts to agricultural impacts, focusing on soil water deficits that can lead to crop failure. Socioeconomic drought describes droughts in relation to water supply and demand. Each of these four types have different models and tools. A more detailed review of drought modelling techniques can be found in Mishra and Singh (2010; 2011).

Meteorological drought: hazard assessments

A plethora of drought indicators and indices quantifying the intensity of droughts exist (Bayissa *et al.*, 2018). The Handbook of Drought Indicators and Indices (WMO and GWP, 2016) highlights some of the most commonly used methods, and is intended for use by, for example, meteorological/hydrological services and ministries, resource managers and other decision-makers at various levels. Multiple authors, such as Keyantash and Dracup (2002) and Zargar *et al.* (2011), have evaluated the performance of these drought indices, and a recent report from the World Bank summarizes the relevant use of different existing drought hazard indices (World Bank, 2019: Table 3.1). The choice of 'drought thresholds' adopted by these hazard indices are often based on expert judgement rather than on observed impacts, and subsequent post-processing is required in order to apply these as drought impact assessment tools. If historic data is available of greater than 30 years and a drought threshold is agreed upon, these indicators can be applied to support real time drought hazard monitoring.

Multiple platforms exist that demonstrate the evolution of these indicators on a continental to worldwide scale in real-time, including the Princeton Climate Analytics platform, US Drought Monitor, European Drought Observatory, African Drought

Observatory, EUROCLIMA Desertification Land Degradation and Drought Observatory for South and Central America and the Global Drought Observatory. For a comprehensive list, see Deltares *et al.* (2018a). These platforms are useful for predicting droughts and provide an indication of the hazard intensity. However, information regarding the timing, duration and extent of droughts, as well as the vulnerability of the area, are required in order to predict the magnitude of the impacts.

Hydrological drought: ecological assessments

Drought is a widely studied driver of ecosystem dynamics, and a recent review on the current state of ecological drought research can be found in Slette et al (2019). Ecological drought risk assessments usually adopt the drought hazard indices approach (Crausbay and Ramirez, 2017) and determine the drought vulnerability of an ecological community, population, individual, or process in relation to the three risk components: exposure, sensitivity, and adaptive capacity (Glick *et al.* 2011). However, risk assessments rarely consider all three of these components (Crausbay and Ramirez, 2017). A few robust examples can be found in Pederson *et al.* (2006), Anderegg *et al.* (2016), Venturas *et al.* (2016), and Lytle and Poff (2004). Kovach *et al.* (2019) recently developed an integrated framework for ecological droughts as a new method to inform natural-resource management.

Agricultural drought: crop production assessments

In 2010, the World Meteorological Organisation (WMO) and the United Nations Office for Disaster Risk Reduction, in collaboration with the Segura Hydrographic Confederation and Spain's Agencia Estatal de Meteorología (State Meteorological Agency), organized an expert group meeting on agricultural drought indices in Spain (Sivakumar *et al.*, 2011). Here, 34 indices used to assess drought impacts on agriculture were listed in seven distinct categories: precipitation-based indices; temperature-based indices; precipitation- and temperature-based indices; indices based on precipitation, temperature, and soil moisture/soil characteristics; indices based on precipitation, temperature, relative humidity, solar radiation, wind speed, and soil moisture/soil characteristics; indices based on remote sensing; and indices based on a composite approach (multiple indicators/indices) (Sivakumar et al 2010: table 1). This list aims to provide a framework for future research.

Such agricultural drought hazard quantifications can be used to highlight statistical relationships between the agricultural landscape and drought dynamics in order to establish vulnerability functions (Luers *et al.*, 2003; Vergeynst *et al.*, 2013). To investigate the effect of adaptation, crop vulnerability curves can be derived for, for example, different varieties and water or agricultural management practices. Alternative approaches quantify vulnerability using semi-quantitative vulnerability metrics, which apply a set or composite of proxy indicators such as land use types or irrigation support (for example, Wilhelmi and Wilhite, 2002 or the USAID FEWSnet program). These vulnerability assessments, in combination with crop harvest exposure data, can subsequently be used to assess current and future agricultural drought risk and the change in risk given certain adaptation measures (for example, Simelton *et al.*, 2009).

Other tools which can be used to assess agricultural drought risk are crop models such as CropWAT or Aquacrop, (FAO crop models). These models, in addition to their ability to quantify crop loss in relation to effective rainfall deficits, also support investigating the benefits of certain agricultural water management adaptation options (for example, Abedinpour *et al.*, 2014).

Socio-economic drought: water and food security assessments

Two techniques to assess socio-economic vulnerability can be distinguished: the use of an index to evaluate vulnerability or the expected outcome approach (EC, MEDA Water, and MEDROPLAN, 2007).

In order to apply the first approach of evaluating vulnerability, a multitude of metrics exists. Some drought vulnerability metrics define vulnerability as "*the predisposition of assets or sectors to suffer adverse effects when exposed to a drought event*" (Smit *et al.*, 1999; Leichenko and O'Brien, 2002; Naumann *et al.*, 2014 and Sanches *et al.*, 2013). Such metrics, in combination with exposure and hazard information, can estimate drought risk in the form of 'likelihood of disaster impact' (for example, Vogt et al, 2016, 2018; Carrao *et al.* 2015). Each metric contains a variety of proxy variables for factors that contribute to vulnerability, normalised and combined into different categories such as economic, human, agricultural and social (Zarafshani *et al.*, 2016; Iglesas *et al.*, 2007).

While the (semi-)quantitative vulnerability indicator approach is valuable for identifying water and food security hotspots and are frequently applied, indices are limited in their application: commonly, the estimation of vulnerability predominately focus on drought frequency and exposure (for example, Polsky *et al.*, 2007) as opposed to separate risk factors. Further, drought vulnerability metrics are often dictated by the availability of data at various scales and it is often hard to establish a cause-effect relationship between the indices and drought disaster databases (Naumann *et al.*, 2014). Finally, the selection of indices' variables and weights are subjective and challenging to test or validate (Luers *et al.*, 2003).

The second, alternative approach is to examine expected outcomes. Bachmair *et al.* (2017) and Blauhut *et al.* (2015) tested data-driven expected outcome models in order to predict drought impacts quantified from text-based reports, such as the reports from the European Drought Impact Report Inventory (EDII) to address the lack of vulnerability estimates. As such, they assume vulnerability to be "*the link between drought intensity, expressed by hydro-meteorological indicators, and the occurrence of drought impacts*" (Bachmair *et al.*, 2017). Models that distinguish different impact categories and have greater quantities of calibration data appear to perform better. Thus, while such approaches would be generalizable for the local to global scale, detailed sectoral impact data for a significant time period is required.

Sutanto *et al.* (2019) and Nobre *et al.* (2019) applied artificial intelligence (AI) algorithms in order to account for and quantify the relationships between observed impacts and drought hazard indices to support future drought impact predictions. Turner *et al.* (2005) and Wossen and Berrger (2015) adopt an agent-based modelling approach (see section 4.1 for more information on agent-based models) to assess risk through estimating the individual household impact of droughts and adaptation decisions. While these approaches provide a potential method to address the scarcity of vulnerability information, generalizability and application on large scales remains a key challenge.

Input data

Depending on the drought type studied and the sector under review, observed and modelled input data derives from both meteorological data, such as precipitation and temperature, and hydrological data, including streamflow and soil moisture, at an hourly to monthly resolution.

Exposure data, such as on population density or livestock, or historic crop yield variability are required for estimations regarding impact levels. Social vulnerability can be estimated in various ways, often requiring data on poverty levels and other household socio-economic information, but also geographic information on local gini-coefficients, which provides an indication of the degree of a society's equality, water infrastructure available or accessibility to markets.

Outputs

Drought hazard models can highlight the likelihood of a drought occurring in an area in terms of probability and return periods. Drought vulnerability models can highlight which areas are expected or found to have the lowest coping capacity and highest sensitivity to droughts. They can also be applied to explore the effect of drought adaptation scenarios. Drought risk models can highlight the likelihood of impact (semi-quantitative) or the expected annual average loss / probable maximum loss if all risk factors are quantified.

Strengths and weaknesses

Strengths	Weaknesses
Social vulnerability to drought as well as drought hazard has been extensively studied and multiple models/formulas exist, tailored per sector and tested for different regions.	The lack of a uniform drought definition and the multitude of hazard and vulnerability indices make it challenging to compare drought management plans across sectors and regions.

Suitability for rapid assessment

Multiple real time drought hazard monitoring platforms exist. However, in order to estimate drought impact, and hence include local vulnerability, a significant quantity of data is required which is currently unavailable. Drought impact prediction models, such as crop models, which have already been calibrated, can be run on a real-time basis. Vulnerability estimates for new regions or crops can be time consuming in order to accurately calibrate and validate. For models with greater complexity, access to significant quantities of data are required through detailed surveying or agronomic research prior to decision making.

Research gaps

Multiple new drought modelling techniques have been developed; however, a key challenge remains to develop transferable methods and strategies between regions (Mishra *et al.*, 2015). Moreover, the lack of consensus on the definition of drought within the drought risk framework remains a challenge (Wilhite and Glantz, 1985). As a result, a lack of standardised methodologies currently hinders the development of Drought Management Plans (Global Water Partnership, 2015).

Further, greater information regarding the ecological and socioeconomic consequences of droughts are required, for example, within the European Drought Impact Inventory[7] (Stahl *et al.*, 2012) or DesInventar[8] (UNDRR) in order to facilitate the approximation of drought vulnerability, predict drought impacts or assess drought risk using quantitative methods. In order to be able to estimate food aid requirements, livestock mortality and country-wide crop failure, generic vulnerability and adaptation models that can be adjusted to local needs should be developed.

Lastly, Integrated Water Resources Management models and socio-hydrological models describe two relationships between the water and human systems. However, no widely used drought adaptation models exist yet. Models integrating different sectors in order to estimate the overall direct economic loss of drought events are rare.

[7] http://www.geo.uio.no/edc/droughtdb/index.php
[8] https://www.desinventar.org/

1.1.3 Forest fires

Forest fire tools and models have been developed for a wide range of management and research applications, from fire danger and risk assessment and management, to decision support systems for tactical and strategic management planning. Depending on the final desired outcomes, temporal and spatial frameworks and data availability, the impacts of climate change on forest fires can be approached and addressed through several modelling methods, including: (i) Fire Danger Rating Systems (FDRS) which are systems used for predicting the future evolution of fire danger through forest fuels; (ii) Fire Models (FM) which simulate the behaviour of fire under current or future climate conditions; and (iii) Integrated Fire-Vegetation Models (IFVM) which generate scenarios of the combined evolution of forests and fires.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).	x	x	
Research	x	x	x
Civil society and NGOs.	x	x	x

These groups of tools and models can be applied to assess various stages of adaptation policy and decision making. FDRS systems, for example, can support the policy cycle at:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risk and vulnerability to climate change

While FM and IFVM models can also support:

- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options.

FDRS highlight favourable conditions for fire ignition occurrences and its propagation through translating climate, meteorological and environmental variables into equations and systems which determine the ease of ignition, rate of fire spread, fire controllability and impact. FDRS are widely used in wildfire prone countries for both scientific and operational purposes. Seasonal forecast and RCM outputs, in conjunction with FDRS, have been also used to analyse future changes in the fire season and danger levels.

FM are useful to predict fire behaviour and fire effects under certain climate/weather conditions. These models were developed to support fire management activities, from fire-fighters training (Heinsch and Andrews, 2010) and prescribed burning, to fuel hazard assessment and forest and fuel management planning. These tools can support managers to evaluate the ideal options for addressing recurrent wildfires, to identify areas at risk and/ or define the optimal treatment options for risk mitigation purposes under climate change (for example, Lozano *et al.*, 2016; Mitsopoulos *et al.*, 2016).

IFVM were developed to assess the combined effect of and interactions between changing conditions on vegetation dynamics and fire regime. Several models were applied at the regional and global scales relating fire occurrence, burned area, and climate change (for example, Kloster *et al.*, 2012; Murphy *et al.*, 2011; Prentice *et al.*, 2011), and have a proven ability to simulate reliable fire regime projections. Migliavacca *et al.* (2013a) applied a refined and optimized version of the Community Land Model (CLM), extended with a prognostic treatment of fires, to capture the complex interactions between burned area, climate, and fuel variability in Europe. A version of this model was subsequently applied to assess adaptation options, such as prescribed burnings and improved fire suppression under climate change projection (Khabarov *et al.*, 2016).

Model and tool methodology

Fire danger rating systems

A variety of FDRSs are described in the literature. Significant, widely applied and tested examples include:

- FWI - Canadian Fire Weather Index of the Canadian Forest Fire Weather Index System (CFFWIS), currently also adopted by the EU Forest Fire Information System (EFFIS) (van Wagner, 1987; San-Miguel-Ayanz *et al.*, 2012)
- KBDI - Keetch-Byram Drought Index (Keetch and Byram, 1968)
- McArthur Mark 5 (Mk5) Forest and Mark 4 (Mk4) Grassland Fire Danger Index (Noble at al., 1980)
- FFWI - Fosberg Fire Weather Index (Haines *et al.*, 1983; Sharples *et al.*, 2009)
- IFI – Integrated Fire Index (Sirca *et al.*, 2007; Sirca *et al.*, 2018).

The FWI is the most widely used FDRS index globally and has been applied to correlate climate change with expected changes in fire severity and damage (for example, Flannigan and Van Wagner, 1991; Bedia *et al.*, 2014; Faggian, 2018). The system is composed of six components which transform input weather/climate data into intermediate codes, which are subsequently exploited to estimate the final aggregated index. Three of these represent fuel moisture codes, while the other three constitute fire behaviour indices.

Fire models (FMs)

In the last decades, several wildfire-spread models and calculation systems have developed (Sullivan, 2009a,b,c), including BehavePlus (Andrews, 2014), FARSITE (Finney, 1998), FlamMap (Finney, 2006), and Wildfire Analyst (Ramirez *et al.*, 2011). The models were developed from observed correlations or physical processes between fire behaviour, such as fire growth and rate of spread, and environmental and fuel parameters including fuel load, wind velocity, and topographic slope. The greatest commonly applied models integrate the Rothermel spread equation (Rothermel, 1972), which computes the steady-state fire spread rate (m per minute) in a plane parallel with the ground surface at every vertex. In order to obtain a spatially explicit calculation of the fire front, different propagation techniques were developed, such as cellular automata or wave propagation modelling.

Integrated fire-vegetation models (IFVMs)

IFVMs study the effect and the interactions of climate variability and climate change on fuel availability and fire regime. The Global FIRe Model (GlobFIRM) can simulate fires at a global or local level, depending on the probability of fire occurrence as a function of daily soil and fuel moisture, and the length of the fire season (Thonicke *et al.*, 2001). The SPITFIRE (Thonicke *et al.*, 2010) model was developed as a combination of the a IFVM and elements of the BEHAVE model, and incorporated into other Dynamic Global Vegetation Model (DGVMs), such as the LPJ-DGVM (Thonicke *et al.*, 2010), LPJ-GUESS (Lehsten *et al.*, 2009), and LPX (Prentice *et al.*, 2011) (see section 2.5 for more information on Dynamic Global Vegetation Models). The Stand-alone Fire Model (SFM) is a version of the CLM-AB fire module, based on a fire algorithm (Arora and Boer, 2005), implemented within CLM (Kloster *et al.*, 2010), and applied to model the burned areas for selected test countries in Europe (Khabarov *et al.*, 2016).

Assumptions

The main assumptions and limitations of these three model groups are based on high-resolution input data requirements (for example, Mallinis *et al.*, 2008; Fried *et al.*, 2008), parameter uncertainties (such as Mitsopoulos *et al.*, 2016; Peterson, 2006) and incomplete representation of all fire processes (Pfeiffer and Kaplan, 2012). As highlighted by Mitsopoulos *et al.* (2016), one of the key uncertainties in modelling future fire behaviour is vegetation landscape change unaccounted for by fire models. On the other hand, IFVMs, which do account for future vegetation/fuels, neglect other important aspects of fire, such as the availability of ignition sources and incomplete combustion (Pfeiffer and Kaplan, 2012). Other limitations of these tools relate to their representation of ecosystem complexity and scale (Herawati *et al.*, 2015).

Model verification

The FDRS can be tested and verified through several approaches, however, considering FDRSs fundamentally rely on weather data while ignitions are frequently caused by anthropogenic actions, assessing the performance of FDRSs are challenging. Andrews *et al.* (2003) and Giannakopoulos *et al.* (2012) apply statistical methodologies to assess and compare the performance of two or more FDRS. A logistic regression was used to validate an FDRS developed in a Mediterranean Basin area (de Vincente and Crespo, 2012). Recently, Pérez-Sánchez *et al.* (2017) applied Mahalanobis distance, percentile method, ranked percentile method and Relative Operating Characteristic curves (ROC) to compare the results of the Angström Index, Forest Fire Drought Index, Forest Moisture Index and Fire Weather Index. Sirca *et al.* (2018) applied a set of statistical tools, including Spearman rank correlation, Index Value Distribution and Percentile Analysis, and Logistic Regression, to evaluate the performance of FDRS by comparing their output values with fire occurrence indicators.

FMs can use historical fire perimeters to verify model accuracy (Arca *et al.*, 2007b; Salis *et al.*, 2013) through the application of Sorensen (Legendre and Legendre, 1998) and Cohen's kappa coefficients (Congalton and Green, 1999). Useful insights regarding the distribution of historical fire sizes are subsequently used to calibrate the fire size distribution with burn periods (Salis *et al.*, 2013; Lozano *et al.*, 2016).

IFVMs can be evaluated against observational fire statistics at a regional level (for example, Migliavacca *et al.*, 2013a and 2013b) using metrics devised by Kelley *et al.* (2013) to quantify the models' performance for individual processes (Rabin *et al.*, 2017). Additionally, the spatial performance of variables is evaluated using the Manhattan Metric (MM) or squared chord distance (SCD); while the temporal accuracy with regards to the timing and length of the simulated fire season can also be compared with observational data (Kelley *et al.*, 2013). Databases, such as the European Fire Database or the Global Fires Emissions Database, could be used for this purpose.

Input data

FDRSs are predominately constructed using meteorological inputs, such as precipitation, temperature, relative humidity and instantaneous wind speed, generally measured at noon local standard time (Lawson and Armitage, 2008). Using climate data and scenarios from GCMs and RCMs, Bedia *et al.* (2014) considered minimum daily humidity and maximum daily temperature as proxies of their noon values, assuming that they are representative of the atmospheric conditions at that time. Climate data and scenarios from GCMs and RCMs are also used by FMs and IFVMs.

In addition to climate data, other variables are required to run simulations. The main FMs and IFVMs require data regarding topography and fuel/biomass, including fuel size, live and dead fuel load, fuel bed depth and moisture content.

Outputs

FDRS outputs are fuel and soil moisture codes and fire behaviour indices related to drought or to the degree of suppression difficulty. With regards to FWI, several studies analysed the outputs in terms of seasonally averaged FWI, 90th percentile of FWI to account for the extreme range of the fire danger spectrum, and the length of the fire season (LOFS), defined as the number of days per year corresponding to the fire season in which the start/end were defined according to the FWI≥15/ FWI<15 threshold values (Moriondo *et al.*, 2006; Bedia *et al.*, 2014).

FMs can predict burn probability, conditional flame length, and fire size, as well as specific indices such as fire potential index, high flame length burn probability, and high flame length probability (for example, Lozano *et al.*, 2016). IFVMs can predict fire occurrence (Thonicke *et al.*, 2001), burned area (Pfeiffer and Kaplan, 2012; Migliavacca *et al.*, 2013b; Khabarov *et al.*, 2016), and global biomass (Pfeiffer and Kaplan, 2012).

Fire danger rating systems (FDRSs)

Schelhaas *et al.* (2010) evaluated the historical and future development of fire risk in European forestry at the national level through a framework combining hazard, exposure and vulnerability. The FWI index was applied to evaluate the hazard, while the European Forest Information Scenario model (EFISCEN V3.1.3) was applied for the development of future exposure and vulnerability under various adaptation measures. Giannakopoulos *et al.* (2014) assessed the vulnerability of Greek Forest to fire risk occurrence through projection of long-term fire related indices (FWI) changes due to climate change, and subsequently identify potential adaptation options within the context of climate change through continuous interaction with local stakeholders.

Fire models (FMs)

Kalabokidis *et al.* (2015), Mitsopoulos *et al.* (2016) and Lozano *et al.* (2017) applied minimum travel time fire simulation algorithms by using the FlamMap and Randig software to characterize the potential response of fire behaviour under climate change at a local and national level respectively. The findings of the three studies can provide information and support decision making regarding fire suppression strategies, fire management planning and fire risk mitigation activities. Although not directly related to climate change, Salis *et al.* (2018) and Alcasena *et al.* (2019) applied fire models to simulate the response of key wildfire activity metrics to several fuel treatments, differentiated in the percentage of treated area, treatment unit size, and spatial arrangement of fuel treatments. The methodology presented in this study can support the design and optimization of fuel and define and virtually test fire and fuel management programs and policies, with the aim to develop comprehensive strategies for risk mitigation and climate change adaptation.

Integrated fire-vegetation models (IVFMs)

Khabarov *et al.* (2016) assessed the potential effectiveness of adaptation options through the standalone fire model (SFM) in Europe. In particular, the study tested fuel removal through prescribed burnings and enhancement of fire suppression, identified by consultation with relevant stakeholders.

Strengths and weaknesses

Strengths	Weaknesses
FDRSs: ▪ provide a useful assessment of future fire danger scenarios through a multi-model ensemble approach (Bedia *et al.*, 2014). ▪ support ignition prevention; fire detection; fire management; adaptation planning through the calculation from historic, current, and future weather/climate expressing the individual; and combined effects of atmospheric conditions and drought. ▪ benefit from regional interpretation and statistical evaluation against historical fire activity. **FMs can provide:** ▪ detailed fire assessments suitable for subnational scales. ▪ graphical output of fire activity	▪ Scarcity of appropriate weather/climate data such as daily means result in systematic negative biases within fire danger calculations (Herrera *et al.*, 2013) and tend to underestimate critical events. ▪ Other fire predisposing factors, such as land use and vegetation, topography, and variables affecting human fire initiation and control, are not included in FDRS calculations. ▪ Some FMs simulate fire behaviour and growth using constant values for fuel moisture and weather. ▪ Many FMs do not identify the probability of fire events. ▪ FMs have poor or missing representation of the long-term

metrics which are easy to understand and useful to inform a wide range of decision-making contexts. ▪ useful information to determine effective fuel treatment locations and can therefore simulate adaptation options. **IFVMs:** • operate at a relatively lower spatial resolution, which is suitable for continent or global assessments.	interaction between fire and vegetation. ▪ Changing vegetation compositions may be complex and unpredictable under future climate conditions (Riley and Thompson, 2017). ▪ IFVMs often oversimplify the fuel and fire spread relationship given that simulations do not account for landscape fragmentation (Khabarov *et al.*, 2016; Migliavacca *et al.*, 2013b). ▪ IFVMs models do not capture large areas likely to burn during years of extreme weather due to (i) an incomplete description of fuel-weather interactions; (ii) fire suppression assumed to be constant in time.

Suitability for rapid assessment

There are different sources of climate input data that can be used for the simulations, such as ERA5 or RCM available on the Copernicus website.[9] Only FDRSs are suitable for a rapid assessment given that FMs and IFVM require a significant quantity of data and require expertise to run the simulations.

Research gaps

The interaction of wildland fire with climate and vegetation over medium to long timespans, such as those required in the assessment of climate change impacts and in the evaluation of adaptation pathways, have significant effects on vegetation dynamics, ecosystem carbon budgets, and patterns of biodiversity. The aforementioned simulation approaches account for an increasing degree of complexity, but in general they oversimplify and do not always accurately represent all climate, landscape, ecosystem and fire dynamics and their interactions. The simulation of a wider range of interacting elements are thus required to further investigate and reflect these dynamics. On the other hand, if the oversimplification was addressed, Keane and Finney (2003) suggested that there will always be a lack of comprehensive data at the scale of application.

Furthermore, even with accurate data, the models and the approaches dependence on initial condition may rapidly degrade the accuracy of the model with multiple non-linear dependencies (Cushman *et al.*, 2007). For example, complex mountainous topography could significantly affect local climate, and therefore local climate impacts, and high-resolution data thus required are not always readily accessible. Additionally, Hoffman *et al.* (2018) suggested that, if process-based models are increasingly used

[9] https://cds.climate.copernicus.eu/#!/home

in wildland fire science, it is crucial to evaluate the ability of models to mimic fire dynamics and effects through the verification, validation and uncertainty quantification.

1.1.4 Land desertification

These models investigate the dynamics of land desertification, which include the effect of climate change, extreme weather conditions and human activities that deteriorate and degrade soil conditions, both in terms of erosion and soil fertility. Land desertification is a major threat across arid, semiarid and dry sub-humid areas, and may negatively impact the provisioning of multiple ecosystem services, including food production and livelihoods.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers		x	x
Investment, finance and insurance.			
Business and industry (private sector).			x
Research		x	x
Civil society and NGOs.		x	x

These models can be applied to assess various stages of adaptation policy and decision making:

- Stage 2: Assessing risks and vulnerability of land uses and soil types to desertification due to climate change and extreme weather events.
- Stage 3: Identifying valuable adaptation options such as land use management that can enhance soil conservation under changing climate
- Stage 4: Assessing potential outcomes of different management options to sustain soil quality, and thus land productivity.

There are several key applications for desertification models:

- Simulating the effects of extreme climate events, such as precipitation and wind, and land use management on soil erosion.
- Dynamics of climate conditions and management options regarding soil fertility and land use productivity.
- Dynamics of climate conditions and management options regarding carbon sequestration/release, and thus climate change mitigation.

The impact of human activities on land has grown exponentially in the Mediterranean, with declining soil structure affecting hydrological cycles over extensive expanses (Kepner *et al.*, 2006). Multiple processes, driven by economic, technological and demographic drivers, have enhanced land degradation leading to desertification (UNCCD, 2009). Areas characterized by recurrent droughts experience sparse vegetation cover and weak soil structure, which can be highly sensitive to extreme rainfall (section 1.1.5) (Wischmeier & Smith, 1978) and wind (section 1.1.6) (He *et al.*, 2011). This results in a high risk of soil erosion and degradation of the soil structure and fertility, leading to desertification (Dregne, 2002). Modelling desertification risk scenarios identifies the effects of climate change, bio-physical and socio-economic factors/ land use scenarios on soil properties, providing potential outcomes which are paramount for informing environmental management strategies (Santini *et al.*, 2010).

Model and tool methodology

There are several modelling approaches using a range of methodologies: from simplified relations, to rough estimations of soil erosion, to more complex dynamics determining the level and changes of soil organic carbon, organic matter and nutrients influencing change in ecosystem productivity.

Water erosion - USLE-type equations

USLE-type equations (Universal Soil Loss Equation) and further revisions (RUSLE, MUSLE, RUSLE2) are simple empirical models providing decision support tools to evaluate soil losses through rainfall erosion (Alewell, 2019). These approaches are based on scaling of key relevant variables influencing erosion and associated parameters, as opposed to description and simulation of soil-hydrology physical processes (Santini *et al.*, 2010). These key parameters are: 1) rainfall-runoff erosivity based on precipitation rates; 2) eroded soil physical and chemical composition; 3) combined topographic slope length; 4) land cover and management; and 5) soil conservation or prevention practices, indicating the anti-erosive effect as a result of soil protection measures to limit erosion, including agricultural conservation practices, ploughing/tilling according to the contour lines and the arrangement of soil in strips. These equations have been applied globally to various environmental conditions, such as with complex topography and at different spatial scales, to derive susceptibility maps as "quantity of lost sediment per unit of surface area".

Water erosion – hydrological basin-scale models

Spatially distributed models combining hydrological water balance and runoff can simulate physical dynamics of different hydrological components, including soil erosion and sediment dynamics (Maidment, 1993). These models are typically developed at the river basin scale to quantify the impact of land management practices on hydrological processes within watersheds, which operate with continuous mass balance equations at daily to sub-daily time steps. In addition to water erosion, hydrology, nutrient dynamics, plant growth, tillage and economics are simulated using physically-based modules to highlight soil erosion risk, for example sediment production, but additionally sediment transport and pathways to spatially derive and distinguish sources and deposition zones (Glavan *et al.*, 2015; Moriasi *et al.*, 2007; Jimeno-Sáez *et al.*, 2018). The runoff simulation and sediment generation can be tracked through overland flows and eventual channel network models. These models can be complex in their articulation but can explicitly highlight the effect of land use and adaptation management practices based on their hydrological position: location in the hierarchy of tributaries within the watershed.

Wind erosion modelling

Wind erosion is a key issue over arid and semi-arid areas, with soil subject to intermittent low-moisture contents and periodic winds (Bullock, 2004). To examine wind erosion risk, models incorporating well-defined relationships (Bagnold, 1941; Owen, 1964; Shao *et al.*, 2003) between surface erosion and wind speed are used, which can define the strength of the erosive acting force of wind on soil particles.

Sandblasting, driven by wind speed, transports soil particles of defined particle sizes. Wind speed is therefore a key factor: its effect is triggered above certain thresholds when it provides kinematic energy able to mobilize particles of increasing size with increasing wind.

In addition to wind speed, these wind erosion processes are influenced by, and can be modelled in relation to, specific land conditions, including soil conditions such as particle size, soil stability, surface moisture and roughness and sheltering effects. These parameters can subsequently be altered within the models to determine the effectiveness of land use management practices and adaptation strategies. Nature-based solutions, through vegetation management, can increase both land surface roughness and sheltering effects which decreases high turbulence wind momentum to provide soil protection from wind erosion (Stockton & Gillette, 1990).

Soil organic matter and productivity assessment model

Land use change dynamics are important anthropogenic sources of atmospheric carbon (Buchholz et al, 2014, Lehmann & Kleber, 2015). Soil organic carbon (SOC) stocks are strongly linked with soil management practices, soil proprieties and climate, including temperature and rainfall (Poeplau *et al.*, 2011, Popp *et al.*, 2014; Reichstein *et al.*, 2013) either releasing carbon into the atmosphere or replenishing stocks through carbon sequestration (Doetterl *et al.*, 2015).

Process-based soil models include biogeochemical processes simulating SOC turnover and implement intra and inter-annual dynamics and spatial combination of climate conditions, land cover and soil properties (Luo et al, 2015; Campbell & Paustian, 2015). These process-oriented models are commonly applied (Smith *et al.*, 1997; Luo *et al.*, 2015; Todd-Brown *et al.*, 2013; Izurralde *et al.*, 1996) and aim to simulate complex soil dynamic processes through emphasizing particular aspects of the carbon cycle, the different compartments and the underlying assumptions. Some models represent the soil as homogeneous, with few soil layers and soil litter treated as a separate component. These assumptions dictate different models' performance ability to mimic long-term trends and required inputs (Izurralde *et al.*, 1996), with some limited due to a lack of detailed management options. The most advanced models (Smith *et al.*, 1997) can simulate biogeochemical fluxes, primary production and water balance on a monthly time step (Parton *et al.*, 1993; Metherell *et al.*, 1993). These support the evaluation of the impact of climate change and ecosystem management, such as the effects of fires, fertilization, irrigation, grazing, various cultivation and harvest methods.

Assumptions

Assumptions and limitations of all of these model typologies are based on reliability of the input data, which describe complex and articulated interactions over space and time between topography, climate, soil and vegetation, and where short but intense events may determine significant outcomes in relation to erosion and land degradation. Thus, time scale is often important to isolate extremes, rather than averages, and models should integrate effects of high variability and extreme climate. There are additional uncertainties regarding climate modelling which underpin the climate parameters required for desertification models.

Physical based models additionally require significant quantities of data to simulate both vegetation properties and the effect of different management options under different land use types. It should also be noted that soil erosion is often a key issue in mountainous areas. However, complex orography presents a greater challenge for model simulations, requiring high spatial resolution and accurate data to simulate greater complexities between relationships such as climate and topography.

Model verification

Model verification requires both observational data of soil properties and sediment transport from multiple long-term datasets and locations for a variety of land uses types. With optimal data parameterization, given the availability of field observations, a good correlation can often be found between model outputs and sites measurements.

Input data

Climate data and projections from GCMs and RCMs, predominately of precipitation and wind, are key input requirements for desertification models. In addition, high spatial resolution soil data are required for physical based models, describing both hydrology and SOC dynamics, which includes soil hydrological properties such as soil water retention, porosity, and hydraulic conductivity, soil development/ soil depth, and soil fertility in relation to nitrogen, potassium and phosphorus concentrations. To conduct accurate assessments, data at the relevant scale are required (Fonderflick *et al.*, 2010) which should have a high spatial resolution, especially in heterogeneous areas such as mountain ranges.

Outputs

Different categories of land desertification models can be implemented to quantify degradation of soil resources. The outcome of these different models provides estimations of soil erosion levels due to precipitation events and runoff, wind and changes in soil organic matter. From this, the effect on soil carbon stocks driven by climate conditions under different land use types and management practices can be examined. Examples of relevant applications of the model groups include:

Modelling soil organic carbon in cropland, grassland and forest soils at global scale (Morais *et al.,* 2019)

The process based RothC soil carbon model has been applied to approximately 17,000 regions globally, with different combinations of soil and climate type and initial land use, to calculate attainable SOC stocks and carbon mineralization rates. The study considered a variety of changes across 80 land use classes, including 28 individual crops and multiple agronomic practices and 16 forest types and pasture, and highlighted how management options and adaptation practices, particularly on agricultural land, could be significantly beneficial to increase carbon stocks and climate change mitigation. Specific implementation of agronomic management functional to adaptation practices could result in significant SOC increases, using crop residues with an average gain of 12 tonnes of carbon/ha, or irrigation at four tonnes of carbon/ha, which are mutually reinforcing effects. This application highlighted effects under near-past climate conditions and SOC gains and losses due to historic land use change, as well as prospective studies for scenario assessment of future land conversions.

Assessment of soil loss by water erosion in Europe (Panagos *et al.*, 2015)

The Joint Research Centre developed a new application, RUSLE2015, as a modified version of the Revised Universal Soil Loss Equation (RUSLE) model to map soil loss estimates for the reference year 2010 at a high-resolution of 100m. This implementation capitalizes on recently available pan-European datasets describing several input parameters such as rainfall erosivity, soil erodibility, cover-management, topography, support practices and vegetation factors according to land use types and management parameters. The mean soil loss rate was estimated to be equal to 2.46 t per ha per year, with a total soil loss of 970 Mt annually in all the erosion-prone lands, such as agricultural, forests and semi-natural areas, in the EU. A significant application of these models have been their role in informing land use based policy scenarios, such as the Good Agricultural and Environmental Condition (GAEC) requirements of the Common Agricultural Policy (CAP) and the EU's guidelines for soil protection under land management (reduced/no till, plant residues, cover crops) and support practices including contour farming, maintenance of stone walls and grass margins. As an example of the analyses developed by this approach, it has been evaluated that policy interventions (GAEC, Soil Thematic Strategy) have reduced the soil loss rate by 9.5% on average in Europe, and by 20% for arable lands over the past decade.

Strengths and weaknesses

Strengths	Weaknesses
Water erosion - USLE-type equations	
USLE and the Revised USLE are the most widely applied soil erosion prediction models for a variety of purposes, and under a variety of conditions as they are the most comprehensive tools currently available (Risse et al, 1993). This approach has a high degree of flexibility and data accessibility with extensive scientific literature and comparability of results. It is largely supported by GIS tools to derive erosion susceptibility maps. Compared to other approaches, they have low input data requirements which are easy to acquire or derive, and it facilitates appropriate and flexible choices according to the study area, data availability and study objectives.	Although widely implemented for estimating rainfall erositivity, several relevant physical processes such as runoff, infiltration and simulation of soil deposition/ sedimentation are not simulated. This approach identifies erositivity or erosion susceptibility but is not capable of modelling the effect of land use management that can facilitate sedimentation and does not distinguish upstream-downstream hydrological links within watersheds.
Water erosion – hydrological basin-scale models	
This approach identifies erosion budgets (erosion and sedimentation over	These modelling approaches can be complex to implement as they require

landscape) and spatial dislocations of soil losses to a greater degree of accuracy, while greater simplified approaches quantify erositivity or erosion susceptibility. The hydrological spatial dynamics distinguish links between upslope and downstream links of adaptation practices, such as nature-based solutions.	significant quantities of input data and parameterization knowledge of the numerous processes simulated. The formatting of the model inputs can also be time consuming. Further, calculations are frequently limited to individual basins, and often cannot be readily applied to large regions.
Wind erosion modelling	
Wind erosion assessments are predominantly based on semi-empirical models which can capture the combined effect of wind and vegetation on wind erosion losses. However, despite uncertainties regarding the parameterization of vegetation coefficients, the models can be simple to apply in wind erosion assessments.	These models are sensitive to parameterization of vegetation, such as vegetation roughness, of which the level of impact and mitigation of wind erosion requires further research. Validation of these models can also be challenging, as there is a strong variability of wind speed and direction in relation to topography and landform that may undermine reliable application at a large scale.
Soil organic matter assessment models	
These are complex models able to simulate the effect of climate and adaptation practices on soil carbon stocks. The effect of vegetation growth on different species or functional types can be determined and thus examine the impact of vegetation management as an adaptation strategy to increase SOC.	These models require high spatial resolution input data of vegetation/crop types and a description of several factors which can be specific for different soil types and vegetation layers. There is often a requirement to describe the vertical section of the soil profile and root allocation, which varies not only for different vegetation types but also with drought conditions. Thus, parameterization processes could be complex, time consuming and require further research to develop accurate relationships.

Suitability for rapid assessment

USLE-type equations are suitable for rapid analyses at large scales. Application of other model types are potentially feasible for the other approaches, but only for small-scale assessments and for vegetation types which can easily be characterized for their physiological and physical properties.

Research gaps

Desertification is a complex process driven primarily by a combination of human activities and climatic variations, which can interact at multiple levels to heighten degradation. The dynamics of multiple interactions between different drivers, however, are not always comprehensively integrated into the models. For example, the effect of different vegetation structures, in particular the spatial patterns of vegetation structures and species composition, are not linked with mathematical solutions to erosion processes and land degradation/conservation. Thus, it is often challenging to generalise the large-scale effects of different vegetation types in order to evaluate the adaptive advantages of different Nature Based Solutions (NBS). Further, vegetation-soil dynamics require significant quantities of data to simulate both vegetation properties and the effect of different management options under different land use types and climate conditions in order to achieve a high degree of accuracy.

1.1.5 Heavy precipitation

Heavy precipitation refers to episodes during which the volume of rain or snow experienced in a location substantially exceeds certain thresholds. Therefore, the definition of heavy precipitation varies according to location and season (EPA, 2016). It is generally evaluated by means of a specific indicator, calculated from daily precipitation data of in-situ observations, modelling reanalysis and future projections (Silliman *et al.*, 2013a,b; Jacob *et al.*, 2014; EEA, 2017).

Users and application

End-users of these models include:

	European	National	Local/Project
Policy and public decision-makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

The evaluation of the heavy precipitation can support the adaptation policy cycle:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options.

Heavy precipitation events can trigger fluvial and pluvial flooding processes, which may have negative impacts on societies and anthropic assets. The assessment of historic trends and future projections of heavy precipitation is therefore required in order to evaluate the flood hazard level, its potential variation as a consequence of climate change, and for advising policy decisions on climate change adaptation and Disaster Risk Reduction (DRR).

Heavy precipitation, which comprises of both high-intensity short-duration events and extended-duration low-intensity events (EEA, 2017), are assessed through evaluating historic trends and future projections to examine variations in their frequency and intensity, and subsequently potential future changes in their temporal and spatial distribution. Based on these expected variations, effective adaptation strategies can be implemented in order to reduce flooding impacts at the regional and local scale.

Model and tool methodology

The spatial and temporal distribution of heavy precipitation can be assessed using GCMs and RCMs, while their historic and future trends are generally assessed by means of specific indicators. The Expert Team on Climate Change Detection and Indices (ETCCDI) (section 1.2.1) have defined a set of 27 climate indices based on daily precipitation and temperature data. Among these, 11 indices are specifically devoted to the analysis of rainfall extremes, including the frequently used index "Rx5d", which defines the maximum annual 5-day consecutive precipitation value.

Within climatic projections, heavy precipitation is generally defined as the 95th percentile of the simulated daily precipitation distribution, in which days with precipitation greater than 1 mm/day are considered. Additional indicators support estimating changes in heavy precipitation return periods (RP).

Future rainfall levels, as well as changes in RP, are used to inform flooding hazard models which supports the identification of flood-prone regions at both the regional (basin) and local (urban) scale. Examples of these models are: i) LISFLOOD-FP model, developed by a joint effort between the University of Bristol and the EU Joint Research Centre; and ii) CADDIES 2D model, developed by University of Exeter.

The calculation of the extreme indices represents an effective climate change proxy and supports the assessment of:

- the frequency of exceedance of a baseline threshold - precipitation thresholds are generally defined using percentile thresholds.
- changes in the volume of rainfall under different climate conditions. In this case, the percentiles can be expressed relative to the overarching distribution of observed precipitation levels, including wet and dry days or hours. Alternatively, a subset of this data could be considered, such as the days or hours with non-zero precipitation and precipitation volume above daily or hourly thresholds specifically computed incorporating observational constraints.

Assumptions

It is assumed that comparisons between historical trends and future projections of heavy precipitation can detect anomalies and subsequent changes in their spatial and temporal distribution. In addition, the frequency and percentile indices used to detect moderate-heavy precipitation events are generally less suitable for detecting rare events; greater sophisticated statistical approaches based on the statistical theory on extreme values are required in these instances (Schär *et al.*, 2016).

Model verification

Models' precipitation projections can be verified through comparison with observational data. Precipitation data are available from in situ weather station observations as well as from remote sensing observations or reanalysis products.

Input data

Heavy precipitation spatio-temporal historic distribution, trends and related indices can be assessed by post processing historical data from gridded observation dataset and re-analysis products, while future climate projections can be obtained by post processing climate modelling data. The majority of the studies investigating trends in extreme rainfall intensity are based on data recorded at a daily resolution, however analysis at the sub daily scale are also important due to the different expected changes in the processes driving convective precipitation compared to large scale precipitation (Scoccimarro *et al.*, 2015; Zhang *et al.*, 2017).

For the assessment of future temporal and spatial distributions of heavy precipitation, high-resolution climate change scenarios using GCMs to provide climate projections accounting for different GHGs concentration scenarios are required. This should also incorporate an assessment of their robustness and uncertainties. GCM results are generally dynamically downscaled by RCMs, which provide a more accurate description of climate variability with a higher spatial resolution.

CPC Unified Gauge-Based Analysis of Global Daily Precipitation, a global observation data set produced by the NOAA Climate Prediction Center (CPC), provides daily precipitation data with a resolution of 0.5° on a regular latitude-longitude grid (Chen et al, 2008). Additionally, historic, present and future high-quality climate datasets are provided by the Copernicus Climate Change Service's Climate Data Store (CDS),[10] which provides a web-platform of freely available climate data.

In order to provide a comprehensive assessment of potential adaptation strategy options, socio-economic data, including the number of potentially affected people within a population, land use and pre-existing blue/green infrastructures, are required in order to evaluate the heavy precipitation resilience potential.

Outputs

The key outputs obtained through analysing precipitation data are indices, such as those proposed by the ETCCDI and related maps. These support the estimation of historic and future trends in spatial and temporal distribution patterns, as well as their temporal evolution. Furthermore, hazard maps can be obtained from flood models.

Several studies have been conducted to assess the change in the spatial and temporal distribution of heavy precipitation at global, national and regional levels as a consequence of climate change. At the global scale, the IPCC (AR5, 2013) highlighted that the frequency and intensity of heavy precipitation events have likely increased in numerous regions, including North America and Europe. These events are likely to increase in their intensity and frequency by the end of the century, particularly over significant proportions of mid-latitude land masses and wet tropical regions.

Scoccimarro *et al.* (2013) highlighted potential changes in the global distribution of heavy precipitation events under a warmer climate using the results of a set of 20 climate models. The study aimed to inspect changes in the upper percentages of the precipitation probability distribution, focusing on the extreme events under warmer conditions between the last decades of the 20th and 21st centuries. This work highlighted the tendency towards greater pronouncement of extreme precipitation in a warmer world, mainly driven by the higher water content expected in the atmospheric column in the future, driving extreme precipitation during deep convection across the majority of the globe.

At the European level, most studies highlight that trends in observed annual and seasonal precipitation (Jacob *et al.*, 2014) differ between northern and southern regions of the continent. In the recent report *Climate Change Adaptation and Disaster Risk Reduction* published by the European Environment Agency (EEA, 2017), trends in maximum five-day consecutive precipitation events for winter and summer periods

[10] https://climate.copernicus.eu/climate-data-store

have been analysed in comparison to the reference period of 1971-2000. These modelled projections indicate an increase in both the frequency and intensity of extreme precipitation events under future climate in Europe. Furthermore, events currently considered as extreme are expected to occur with greater frequency in the future (EEA, 2017). These results can be useful for informing decision-makers and supporting them in the selection of suitable adaptation measures to be applied to sensitive areas, infrastructure, (section 2.9) and buildings (section 2.10).

Strengths and weaknesses

Strengths	Weaknesses
Climate change analyses concerning the assessment of variation in magnitude and occurrence of heavy precipitation can be exhibited using synthetic indices such as those proposed by the ETCCDI, maps and graphs, largely shared by different communities: research, policy and private sectors.	Observational data: limited availability of high-resolution spatial and temporal data; Projected/simulated data: Uncertainties associated with climate models are primarily due to different emission scenarios, model parameterization, and dataset reliability.
	In some EU countries, data records are short and contain poor spatial resolution.
	Data is currently not freely shared.
	Models generally have a high accuracy in detecting the spatial distribution of extreme precipitation events but underestimate their intensity, especially in complex orographic regions predominantly due to their spatial resolution.

Suitability for rapid assessment

The first level of percentile analysis, in order to identify regions and periods prone to extreme events, can be conducted accessing existing and readily available large datasets, such as EURO-CORDEX data through the Copernicus CDS platform.

Research gaps

The main gap associated with the assessment of heavy precipitation, especially at a local scale, is the lack of long-term readily available data records. Moreover, precipitation patterns are influenced by local factors which are supported by data from a large number of in situ weather stations and can permit greater detailed analysis, especially in complex orographic regions. According to a recent assessment carried out by EEA (2017), Europe currently only collects data through terrestrial rain gauges. In Southern and Eastern Europe, these have only recently started to accumulate data. Furthermore, remote sensing techniques are also used to complement observational measurements, as demonstrated by RADKLIM dataset provided by the German Weather Service.

The higher spatial and temporal resolution of GCMs has increased the confidence of climatic projections, providing greater accuracy in simulations of extreme events (Giorgi *et al.*, 2014). Nevertheless, the resolution of RCMs (10-30 km) is generally too coarse to capture sub-daily extreme events (Ban *et al.*, 2015). A new generation of Convection Permitting (CP) RCMs is currently being investigated by different projects (H2020 EUCP) and initiatives (FPS CORDEX CP) aiming to predict localized intense precipitations at a sub-daily scale.

1.1.6 Windstorms

Currently, European windstorm footprints are directly derived from climate model outputs. Whilst there exists a wealth of methodologies for tropical cyclone wind field parameterization modelling from a set of variables, such methods have not been developed for mid-latitude storms yet.

Users and application

Users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.			

Wind models can inform various stages of adaptation policy and decision making:

- Stage 2: Assessing risks and vulnerability to climate change
- Stage 4: Assessing adaptation options

Wind models can inform decision-makers, risk modellings and urban planners to identify locations that may be exposed to high wind speeds. This will allow them, for instance, to identify the appropriate level of protection and design standards required for infrastructure and buildings.

Model and tool methodology

Modeling the spatial footprint of windstorms is difficult. For tropical cyclones, there exists a wealth of methodologies to derive a 2D-parametric wind field from track data (for example, Holland, 1980; McConochie *et al.*, 2004, Cardone and Cox, 2009). These models commonly utilise information on mean sea-level pressure, maximum wind speeds, size of the eye, and longitudinal and latitudinal position to derive a symmetrical, circular wind field around the center of the cyclone. Finally, by adding a background wind, the asymmetric wind field is created (Lin and Chavas, 2012). Such models are commonly validated against wind speed observations. For extratropical cyclones of mid-latitude regions, however, such parametric models have yet to be derived. This is because the shape of an extratropical cyclone (typically "comma-shaped") and smaller-scale wind intensifications such as the sting jet (see Browning 2006 for more details), complicate the capturing of the spatial footprint of such storms in a series of formulas. Instead, a widely used approach to derive spatial footprints of historical events is to extract wind speed/ gust information from (regional) climate models (for example, Darce *et al.*, 2012, WISC[11]), or to use observational data (Browning, 2006; Bonazzi *et al.*, 2012). However, as these wind fields are part of the output of such models rather than a methodology in itself, see outputs for more detail.

[11] https://wisc.climate.copernicus.eu/wisc/#/help/products#footprint_section

Another type of hazardous windstorms are the Mediterranean tropical-like cyclones, also known as Medicanes. Medicanes show similarities to tropical cyclones in the sense that they often also form an eye and have a circular wind pattern. Comparable to extratropical cyclones, there does not exist a methodology yet to parameterize the 2D-wind field of a medicane, and most studies have used observational or model data to analyze the wind footprint (Pytharoulis *et al.*, 2017; Nastos *et al.*, 2018). However, as Medicanes show spatial analogies to tropical cyclones, the design of a possible 2D-wind field parameterization could follow a similar approach as the methodology established for tropical cyclones.

Input data

2D-wind field parameterization models used for tropical cyclone wind field modeling require information on the track of the tropical cyclone (longitude/latitude), minimum sea-level pressure (in hPa), maximum wind speeds (m/s), the radius to maximum winds (size of the eye; in km) (Holland, 1980).

Output

The 2D-wind field parameterization models used in tropical cyclone research output the maximum wind speed and minimum sea-level pressure at every grid cell in a polar grid fitted around the eye of the tropical cyclone. The spatial resolution of these grid cells is not fixed, but are often chosen between 1-10 km. The temporal resolution commonly matches the resolution of the input dataset, which is often either hourly, three-hourly, or six-hourly data.

These 2D-tropical cyclone wind field data can serve as input for hydrodynamical modelling (storm surge, waves) (Lin and Chavas, 2012) and input for wind speed probability and damage assessments (Bloemendaal *et al.*, in review).

2D-wind field data, with information on maximum wind speeds, is the starting point for wind damage assessments. Recent examples are Koks and Haer (2020) and Welker *et al.* (2020), who used pan-European datasets of winter storm events (WISC[12]) to assess the potential damage to buildings as a result of extreme wind.

Strengths and weaknesses

Strengths	Weaknesses
▪ Due to the usage of basic information on the intensity and path of the tropical cyclone, the 2D-wind field methodology can be easily applied anywhere in the world. ▪ 2D-wind field data can assess high-resolution wind risk and damages and can serve as input for hydrodynamical modelling (storm surges, waves).	▪ Method is currently only designed for tropical cyclones; extratropical cyclones follow different spatial properties, hence they cannot be modelled the same way. ▪ Parameterization does not capture topographic effects on the tropical cyclone wind field, localized differences in the wind field are smoothened out in the process.

[12] https://wisc.climate.copernicus.eu/wisc/#/help/products#footprint_section

Suitability for rapid assessment

At the event scale, 2D-wind field parametrization models are quick to run to provide rapid feedback to decision makers or to serve as input for other models.

Research gaps

A similar parameterization scheme is lacking for extratropical cyclones and Medicanes; wind damage assessments from extratropical cyclones is currently only possible through climate model output datasets.

1.1.7 Hailstorms

These models are used to quantify and evaluate the potential risks associated with hailstorms. This information can be used for a greater understanding of the relation between meteorological/climate conditions and associated risks, as well as improving the prediction of hail events.

Hail risk models can commonly be divided in two main methods and applications: i) the prediction and simulation of hailstorms using historical information, remote sensing or numerical modelling; ii) the assessment of hail risk and vulnerability by overlaying the information of numerical/stochastic models with exposure maps and damage functions.

Users and application

Users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).			
Research			
Civil society and NGOs.			

These models can be applied to assess the following stages of the adaption policy cycle:

- Step 2: Assessing physical risks and vulnerability of property to hailstorms.
- Step 6: Monitoring and evaluating of the characteristics and development of previous and future hailstorms and the resulting damage, if any.

The outputs can be used to identify areas that are prone to hail impacts. With increasing predictability of hailstorm occurrence and severity, several applications in terms of climate adaptation can be adopted by different stakeholders:

- Agricultural diversification by farmers.
- Localized premiums and risk management for the (re)insurance industry.
- Hail protection measures to wind shields, windows or other property, such as solar panels or roofs.

The models produce annual probabilities of the frequency and severity associated with hailstorms. The severity of hail is commonly defined by the diameter of hailstones in the case of numerical models but can also be measured in terms of financial losses by damage models.

Model and tool methodology

Prediction and simulation models

The Hail Detection Algorithm (HDA) as suggested by Witt *et al.* (1998) is used to compute hailstone proxies that refer to the expected hailstone diameter (mm). This model can calculate the probability and severity of certain hailstones based on radar and weather input. The results can be used to create time-series and climatologies that represent the physical hail risks in regions. Assumptions are made on the climate and reflectivity parameters used as input (Witt *et al.*, 1998).

Risk and damage models

An example for European damage models is the AIR severe thunderstorm model[13] or the Risk Management Solutions (RMS) HailCalc. Damage models offer regional insurers of hail risk, and automobile insurers, the possibility to model hail damage. These kinds of models are suitable for commercial building insurance, industrial and residential use, private house insurance and agricultural exposure. The model leverages multiple data sources to capture the risk from hail and straight-line wind in a hybrid physical-statistical approach.

Input

The HDA utilizes radar-data in combination with meteorological parameters. These parameters are usually derived from numerical weather models such as High Resolution Limited Area Model (HiRLAM), that include surface pressure, atmospheric temperature, wind, and humidity. Radar data is often available in different formats, varying in temporal and spatial resolution. For the Netherlands, radar composites are publicly available with a temporal resolution of five minutes and a spatial resolution of $1km^2$.

Risk and damage models leverage historical weather data from a range of sources, including local storm report databases such as European Severe Weather Database (ESWD), Europe weather radar data and atmospheric reanalysis data. The model’s damage functions are based on engineering analyses of construction practices, country-specific building codes, and claims data.

Output

The main output of hail prediction models are spatial maps that contain information on the physical impacts of hail. By creating a climatology of historical events, the spatial and temporal impacts of hailstorms on society can be investigated and used to inform decision making in the public as well as private domain. An example is the recent study to the vulnerability of solar panels. Local hailstorms were used to relate simulated hailstone proxies to solar panel damage and used to assess future potential of solar panels in the Netherlands (Teule *et al.*, 2020).

In the case of damage modelling, the output often includes stochastic event catalogues that are coupled with exposure maps (AIR offers a $1km^2$ industry exposure database) to provide projections on annual or individual storm damage. These are generally derived from insurance loss data collected by insurance companies.

[13] https://www.air-worldwide.com/models/severe-thunderstorm/

Strengths and weaknesses

Strengths	Weaknesses
▪ Outputs can provide insights regarding physical hail hazards at a regional level. ▪ Input data or results on hail hazards in the form of spatial maps are often openly available. ▪ Models with damage functions can quantify hail risk.	▪ There is a lack of hazard simulation models that are linked to societal impacts, such as economic quantification. ▪ The effect of climate change on the physical hazard of hail remains to be quantified. ▪ The competitive nature of the insurance industry hampers the transparency in damage models. ▪ Severe hailstorms are currently a rare and localized phenomenon. Therefore, validation of the models is challenging.

Suitability for rapid assessment

Because of the data-requirements and the requirement of technical expertise to analyse the data, the process of using these models is often time-consuming. Graphical hazards maps are generally made available by meteorological offices or researchers, which can be combined with local exposure maps. However, detailed vulnerability to hail, often communicated as damage functions, are currently not available open source.

Research gaps

Research gaps include:

- Quality of hailstone observations for model validation.
- Consistent damage reports that are focused solely on hail damage
- Development of socio-economic projections on hail by coupling hazard with exposure and vulnerability.

Severe hailstorms are characterized by rapid on-set and highly localized impacts. Therefore, collecting data for calibration or validation remains extremely difficult. Simulated hailstone proxies can be validated with ground reports of observed hailstones. Projected hail damage can be validated with insured losses which are often collected by insurance companies through damage claims.

Currently, there is also a research gap regarding comprehensive models for the adaptation of hail impacts. Risk and vulnerability models are used by (re)insurance companies in order to assess their portfolio risks. However, there are currently no ‘open’ models that indicate the impact of climate change on hail occurrence or that can test the impact of adaptation strategies against hail damage.

1.1.8 Flow and river flow

Flow and river flow models can be broadly categorised into two groups: hydrologic and hydrodynamic models. Hydrologic models are tools that perform mathematical representations of hydrological processes, such as rainfall-runoff and infiltration of water into the soil; hydrodynamic models are tools which simulate the motion of fluids, usually of water, which are useful for understanding and characterising flood events.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.	x	x	x

Flow and river flow models can contribute to the adaptation policy cycle at:

- Step 1: Preparing the ground for adaptation
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options.

Flow and river flow models have been extensively used for assessing the impacts of climate change on flood hazard at different spatial scales. These assessments support the examination of complex human-water interactions in river basins, which can also inform regional impact and vulnerability assessments, among other applications. These models are capable of providing useful information to support the prioritization of adaptation strategies which can reduce rainfall-runoff in river basins, such as land use change, retention basins, and some nature-based solutions.

Model and tool methodology

Hydrologic models

Hydrologic models are commonly designed to simulate hydrologic processes occurring in watershed systems, such as rainfall-runoff, river flows, infiltration rates and groundwater recharge over extended time periods, ranging from months to years. These models can be broadly categorised as either stochastic or deterministic models. Stochastic models are data intensive, relying, for instance, on an empirical model that aims to reproduce observations through simulation of a second observational dataset. Deterministic models are, in contrast, highly parameterised, requiring information regarding the spatial discretization of the watershed including soil information, land use data and river networks, and are usually classified as lumped, semi-distributed or fully distributed models. A lumped model considers the watershed as a single spatial unit, while a distributed model subdivides a watershed into smaller, spatially defined units. A fully distributed model spatially discretizes a watershed into regular cells/

pixels, while a model is classified as semi-distributed when a watershed is spatially discretized into smaller lumped areas such as hydrologic responsive units (HRUs).

Some hydrologic models, such as the Soil and Water Assessment Tool (SWAT), provide additional functionalities such as the simulation of land management impacts on water, sediment and agricultural chemical yields. These hydrologic models that provide additional functionalities are suitable for assessing proposed adaptation strategies which might impact the terrestrial hydrological cycle. However, these models usually simplify hydrologic cycle processes, and therefore a trade-off based on the end-user priorities' is required. Other common hydrologic models include HYPE (HYdrological Predictions for the Environment), HEC-HMS, and LISFLOOD (Distributed Water Balance and Flood Simulation Model).

Hydrodynamic models

Hydrodynamic models, on the other hand, are suitable for simulating the floodplain inundation process, such as flood extension, water depth, and flow velocity, and are essential instruments for supporting the decision-making of adaptation strategies in areas that are exposed to flooding. They often specify a domain/ area of interest, in which the flow dynamics are simulated. These model domains have three key requirements: i) the spatial discretization of the domain, which in turn requires a mathematical method to solve spatial discretization problems including finite difference and volume methods; ii) initial information regarding each spatial element of the domain; and iii) information regarding the behaviour on the boundaries of the domain, which are required at the beginning and throughout the simulation timeframe. The specific information required varies for instance, the ANUGA models requires information regarding the water stage, bed elevation and friction, which can be used to predict the impacts of hydrological disasters such as riverine flooding, storm surges and tsunamis. Further examples of hydrodynamic models include LISFLOOD-FP and HEC-RAS.

Assumptions

Model assumptions vary based on model type, mathematical assumptions, processes considered, and model technique.

Model verification

Flow and river flow models are commonly validated against controlled experiments, observation events, and field studies, where available. Examples include the validation of the ANUGA model using a wave tank experiment for the Okushiri 1995 tsunami, wave tank run up experiments at the University of Queensland, and the 2004 Indian Ocean tsunami impact at Patong Beach. Moreover, models are often compared to other models to check their performance and reliability.

Input data

Data requirements vary by location and application and require locally collected data based on the application of interest. Some open access databases exist, such as the Copernicus Climate Data Store.[14] Hydrodynamic models usually require water level

[14] https://cds.climate.copernicus.eu/#!/home

flow dynamics, such as horizontal momentum, at both the initial and boundary conditions. Information pertaining to the soil type and land use classes are also relevant, as these influence the friction levels and are important for flow models. Moreover, information regarding the topography is also fundamental in order to emulate the flow channels inside the domain.

Hydrologic models commonly require data regarding the topography, land use, soil, channel geometry, and meteorological conditions. The key meteorological data required are precipitation and air temperature, while other variables such as solar radiation, relative humidity, wind speed and evapotranspiration can also be used to better simulate the hydrologic cycle.

Depending on the application, socio-economic data may be required. For instance, SWAT is designed to predict the impacts of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over extended time periods. Consequently, this model requires data on land management and water requirements for irrigation, among others.

Outputs

Common output information includes streamflow; flood hazard characterisation including flood extension, water depth, and flow velocity; and hydrographs. Flow and river flow models often provide output results as a series of text files which can be read by any text editor and imported into data management software, or as specific file formats such as .sww for ANUGA or .tss for LISFLOOD. However, the data provided by these models are often complex to interpret and require technical expertise. Some models, such as LISFLOOD-FP, provide outputs in relatively simple file formats such as ArcGrid ascii, while SWAT requires auxiliary tools such as SWAT Check to facilitate the reading of the model outputs. Other models require a post-processing step in order to convert the data to a more user-friendly format.

LISFLOOD and LISFLOOD-FP has been used as a research tool within the pre-operational European Flood Alert System (EFAS) at the EU Joint Research Centre. Supported by the results provided by LISFLOOD, EFAS provides warning notifications twice per day to the corresponding EFAS partners to inform them of a possible flood event. Moreover, EFAS issues formal flood notifications when: i) the probability of exceeding critical flood thresholds is forecasted greater than 48 hours in advance; ii) the river basin is part of an EFAS partner, and; iii) the catchment has a minimum upstream area of more than 2000 km^2. Additionally, the forecast requires persistence and at least one deterministic forecast needs to exceed the EFAS 5-year return period of a high flooding threshold. EFAS is part of the Risk Assessment for Strategic Planning (RASP) tiered methodology for flood risk assessment, developed on behalf of the Environment Agency of England and Wales and UK's Department for Environment, Food & Rural Affairs (DEFRA), as well as for research studies at a number of institutions, including Ohio State and the University of Washington, USA and the University of Messina, Italy.

HYPE has been used in the Sustainable Urban Development Planner for Climate Change Adaptation (SUDPLAN), an EU FP7 project combining computer technology and environmental knowledge. The E-HYPE model, the Pan-European high-resolution application of the HYPE model, is a hydrological model developed by the Swedish Meteorological and Hydrological Institute (SMHI) for both small-scale and large-scale assessments of water resources and quality. It has additionally been used as the hydrologic model of the Service for Water Indicators in Climate Change Adaptation (SWICCA).[15] SWICCA is a big data initiative which manages climate change adaptation within the water sector, predominantly providing data and guidance for climate impact assessments.

Strengths and weaknesses

Strengths	Weaknesses
Both hydrologic and hydraulic models are suitable for supporting decision-making in a variety of applications, including flood forecasting; assessing the effects of river regulation measures; assessing the effects of land-use change on the hydrologic cycle and flood hazard characterisation; and assessing the effects of climate change, among other applications.	These models require significant quantities of data for calibration purposes, user familiarity with the subject and the model, and specific knowledge regarding the area of study.
Hydrodynamic models that can simulate water presence and movement are particularly useful for flood hazard assessments, as they can, for example, simulate water inundation around developed environments.	Fully distributed hydrologic models or 2D/3D hydrodynamic models are usually computer intensive.
Hydrologic models, such as the HEC-HMS model, can subsequently support decision-making in highly developed urban watersheds.	

Suitability for rapid assessment

Due to the large number of available flow and river flow models, access to input data and/or previous studies is often straightforward. However, most models require a long-term study in order to identify the necessary datasets and for calibration and validation of the models. Moreover, depending upon the complexity of the specific model application, data availability and the user's familiarity with the model, some models may be better suited than others.

15 https://climate.copernicus.eu/sites/default/files/repository/Events/SIS_Meeting/SWICCA_2.pdf

The rapid use of models and methods of flow and river flow models vary according to model type and assumptions. However, the majority of these are rapid to use providing that the data requirements are identified, and the model is calibrated.

Research gaps

During the past few decades, the number of locally available and remotely sensed datasets required to force and parameterize flow and river flow models has significantly increased. Moreover, a growing number of global datasets providing vital information to run these models are available, such as HYDRO1k - 1km hydrological DEM and drainage network derived from GTOPO30[16], and ERA5 hourly meteorological forcing from ECMRWF reanalysis of 1981-current.[17] However, a key gap within these pertains to the quality of the available data. Hydrologic models, for instance, usually require large observational datasets in order to adequately calibrate and validate the model. Additionally, hydrodynamic models require specific data pertaining to a particular flood event in order to replicate these. As such, the data requirements include water level changes during a period of hours and/or days during the specific flood event, however this information is rarely available from Earth observations.

A further key gaps of flow and river flow models pertains to their spatial resolution, which, in turn, depends on the extent of the model domain. Ideally, these models should target the utilisation of unstructured grids, as those provide a more flexible connection between the upscaling and downscaling of model parameters to the underlying topography. Another dimension that needs to be considered is the temporal dimension: when applied to support decision-making in the context of climate change adaptation, flow and river flow models need to be capable of providing estimates of historic and current states of the hydrologic cycle and under different climate conditions. Moreover, these models also need to be robust while flexible enough to be coupled with other families of models, such as for the simulation of the interactions of the hydrologic cycle with the earth and human system(s).

Additionally, research needs to expand to examine the effects of policy-induced or autonomous behavioural changes in human systems which may affect water and land management. Further, examining these changes in water cycle dynamics and consequential management of water resources at a basin scale is not feasible without additional consideration for the interactions and feedback between natural and human systems. This new area of research has subsequently established the study of "socio-hydrology" (Sivapalan *et al.*, 2012). Human impacts on the terrestrial hydrological cycle are estimated to be significantly greater than climate change, particularly at the local scale. Most hydrologic models, however, do not consider the effects of a co-evolution human-water system, but alternatively model human impacts as an external force on the hydrologic cycle. As such, it is imperative that this area of research is developed.

[16] https://lta.cr.usgs.gov/HYDRO1K
[17] https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview

1.1.9 Landslides and avalanches

This chapter provides a review of the methodological approaches for the assessment of climate change impacts on slope stability and rainfall-induced landslide dynamics.

Users and application

End-users of these include:

	European	National	Local/Project
Policy and public decision-makers	x	x	x
Investment, finance and insurance	x	x	x
Business and industry (private sector)	x	x	x
Research	x	x	x
Civil society and NGOs	x	x	x

Assessments of climate impacts on slope stability and landslide dynamics can support the adaptation policy cycle in the first three steps:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options.

The hydrological cycle is strongly affected by climate change and directly impacts on the piezometric regime of natural slopes and their stability conditions (EEA, 2017). Therefore, assessments in order to identify potential spatial and temporal variations in landslide hazard levels are paramount, providing fundamental research to support decision-makers in selecting operative management actions and defining recommendations for the implementation of effective management strategies aimed at increasing local adaptation and mitigating overall risk.

Model and tool methodology

A desk review conducted by Gariano and Guzzetti (2016) identified two approaches to assess the variations in slope stability and landslide dynamics potentially induced by climate change. The modelling approach investigates variations in relation to long-term projections of atmospheric forcing of primary precipitation and secondary potential evapotranspiration, which are adopted as input data for physically based or statistical slope stability models. In this case, models translate weather forcing into hydrological variables related to slope stability. Such an approach is usually applied to analyse a slope section, a single slope or a single landslide (for example, Comegna *et al.*, 2013; Rianna *et al.*, 2014, 2017), and are also suitable for the investigation of several slopes located in homogeneous areas (Chang and Chiang, 2011; Ciabatta *et al.*, 2016).

The second method uses an empirical approach that evaluates the spatial and temporal variations of landslide dynamics (occurrence, frequency and rate of re-activation for deep rainfall-induce landslides) based on correlations with historic precipitation and temperature records and paleo-environmental data. While the modelling approach is most suitable for evaluating landslide occurrence under future climate conditions and for supporting the adaptation framework, empirical approaches are useful for supporting "what-if" analyses as they support the evaluation of landslide characteristics under historic climate conditions.

Assumptions

A key assumption of slope stability models is that the range of historical conditions which have previously triggered rainfall-induced landslides will continue to match future conditions for landslides.

Model verification

The quality of the results of the modelling approaches can be evaluated by reproducing past landslide events occurred in the targeted areas. Specifically, spatially distributed slope stability models are calibrated and tested using rainfall measurements and landslide information obtained from historic events (Guzzetti et al, 2020).

Input data

Specific climate data used to assess slope stability and rainfall-induced dynamics varies according to individual methodologies, however, the key underlying parameter is precipitation. Greater detailed evaluation with sophisticated physically based approaches also requires air temperature in order to calculate evapotranspiration potential and soil hydraulic, mechanical and thermal properties.

Future precipitation and temperature projections are simulated using Global Circulation Models (GCMs), driven by specific Representative Concentration Pathways (RCPs), and downscaled on a limited area by applying one of the available downscaling techniques (dynamical or statistical). Historic, present and future high-quality climate datasets are provided through the Copernicus Climate Change Service's Climate Data Store (CDS),[18] a web-platform providing freely available climate data.

Further socio-economic inputs for landslide hazard assessments should include changes in land use and land cover given that they can affect, directly and indirectly, landslide occurrence through altering the hydraulic and mechanical soil proprieties. Additionally, demography changes can inform the number of people potentially at risk.

Outputs

The outputs of these models include graphs which can indicate landslide occurrence in relation to predisposing and triggering factor thresholds. For example, these graphs could highlight antecedent/cumulative precipitation against daily/trigger precipitation for shallow landslides; displacement-antecedent precipitation for deep landslides; and intensity/duration curves. Furthermore, model outputs can also provide maximum threshold values which can be used to develop early warning systems. Additionally, maps can also provide the spatial distribution of both landslide susceptibility and hazard levels.

[18] https://climate.copernicus.eu/climate-data-store

Model-based simulations highlight that climate change is expected to vary the frequency and intensity of weather extreme events (IPCC, 2013) and that variation in heavy precipitation patterns will potentially affect the occurrence and frequency of landslide events (IPCC, 2012) and the extent of the area at risk (Ho *et al.*, 2017).

Accounting for the evaluation of slope stability conditions based on downscaled climate projections, several studies have been carried out to investigate the effect of climate change on landslide occurrence. Most of these studies were conducted in the French, Italian and Swiss Alps, since mountains respond to climatic change faster than other territories (Beniston, 2003). Furthermore, a recent study has generated a map of variations in landslide frequency and activity based on an ensemble of GCMs driven by different climate scenarios (Gariano and Guzzetti, 2016; EEA, 2017). The study highlights that an increase in rock falls, debris flows, and shallow landslides are expected by the end of 21st century under the climate conditions estimated for the scenario RCP8.5.

At a local scale, Gariano *et al.* (2015) proposed a method for evaluating future variations in the occurrence of rainfall-induced landslides in response to changes in rainfall regimes. This study investigated a number of rainfall-induced landslides in Calabria (southern Italy) between 1981 and 2010 in correlation with daily rainfall data. In addition, further analyses conducted using the same framework accounted for the high-resolution climate projections based on RCP4.5 and RCP8.5 scenarios in order to evaluate the mean variation in annual rainfall, seasonal cumulated rainfall, and the annual maxima of daily rainfall for 2036-2065 compared to 1981-2010. Based on these analyses, the authors investigated the relationship between historical heavy precipitation and landslide frequency and subsequently how it could change under future climate conditions.

Finally, a recent study examined a number of regional, national, and global Landslide Early Warning Systems based on forecast models, including rainfall thresholds, distributed slope stability models, and soil water balance models (Guzzetti *et al.*, 2020). These tools are considered among the most effective ways to reduce rainfall-induced landslide risk.

Strengths and weaknesses

Strengths	Weaknesses
The models support the identification of adaptation and mitigation measures tailored to local conditions such as the local geological and geomorphological setting and local variations in climate extreme events.	Further changes in landslide occurrence are also linked to changes in human activities and land use that can be challenging to model.
The local scale investigation of the landslide occurrence can be supported by physical-based models.	Uncertainties associated with climate models used to obtain data series for the analysis of the local weather extremes, predominately due to

	different emission scenarios, model parameterization and dataset reliability.

Suitability for rapid assessment

Data is readily accessible: rain gauge networks, meteorological models and weather radars provide climate data required for applying landslide models and satellite estimates. Historic and future climate information is also free available on the Copernicus Data Store platform.

Some of the available rainfall-induced landslide models, such as those based on thresholds, are suitable for a rapid assessment of the landslide hazard under future climate conditions.

Research gaps

One of the main gaps is the lack of information regarding the indirect factors that affect the landslide re-activation, such as forest fires, land-use change and increases in soil fracturing. Additionally, the majority of the regional studies carried out are aimed at evaluating the landslide susceptibility and hazard. Furthermore, they can provide information on how climate change can affect the landslide spatial and temporal distribution but cannot assess the effectiveness of adaptation strategies.

1.1.10 Coastal and sea level rise

Coastal hazard models estimate the magnitude and geographical extent of different coastal hazards such as coastal flooding and erosion, both for the current climate, and future conditions induced by anthropogenic climate change. Extreme winds and salt-water intrusion have been excluded though. Results from these hazard assessments inform impact models to determine the risk to society.

Users and application

End users include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.		x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.		x	x

These models can be applied to assess various stages of adaptation policy and decision making:

- Stage 2: Assessing risks and vulnerability of assets located in the coastal zone associated to coastal hazards, such as flooding and erosion, that can be enhanced by climate change
- Stage 3: Identifying adaptation options that reduce risks and impact of coastal hazards
- Stage 4: Assessing adaptation options by modelling measures and comparing risk reduction

Risk information, as determined through relevant hazard modelling combined with exposure and vulnerability information, can be expressed as annual economic losses or the number of affected entities. This information be used by different stakeholders to compare risk reduction/ adaptation strategies. Depending on individual cases or circumstances, these measures could, for example, include the establishment of infrastructure safety standards or insurance rates (including premiums) to transfer risks.

Model and tool methodology

When modelling and assessing adaptation options to reduce coastal hazards and impacts, there are several methods that can be used, depending on the scale and type of hazard analysed.

Flood hazard

To assess flood hazard at a global or continental level, a simplistic approach is required due to the large computational time required to accurately simulate the inland flooding extent and magnitude. Normally, a static inundation approach, also known as “bathtub fill”, is used. This method assumes that all continental land lying below a certain water level (mean seal level) will flood if the area is hydraulically connected to the sea (Paprotny *et al.*, 2018).

At a regional level, fast flooding solvers can be used to assess the hazard. Such fast flooding solvers adopt alternative methods to resolve detailed hydraulics which increases the computational efficiency of the models, making them attractive for quick assessments, probabilistic analysis frameworks and forecasting purposes. Due to the computational efficiency of these models, different adaptation options can be tested in the model. Sea level rise (SLR) projections can be easily incorporated by increasing water levels.

The most advanced modelling techniques are made up of physical-process models. In these models, the different relevant processes, either of the hydrological cycle or of relevant hydrodynamic and transport mechanisms, are specifically represented by the mathematics and physics of each process, with equations solved for each time step and grid of the model according to the relevant forcing mechanisms. This type of model is recommended when there is sufficient data for the construction, calibration and validation of the model. Due to the complexity and dynamic interaction of different processes, computational time can be high depending on the extent and grid configuration.

Coastal erosion

At a global scale, shoreline change projections can be used to estimate the associated land loss due to storm events and long-term processes such as SLR under different climate projections. The database EC-Joint Research Centre (2019) includes global estimates of SLR retreat for sandy coasts, computed using the Bruun Rule (Cooper and Pilkey, 2004; Ranasinghe and Stive, 2009). It also includes estimates for storm retreat (based on Kriebel and Dean, 1993) and a so-called “ambient change” which indicates shoreline change from factors other than climate change.

Aside from the Bruun Rule, other parametric models can be used to estimate coastal erosion at a regional level. Parametric models are defined by a finite set of parameters which are used to predict future data. These types of models often manage discrete values. These models estimate storm-induced erosion using two different approaches. The first one estimates erosion based on storm conditions and beach characteristics (Mendoza and Jimenez, 2006). The second approach uses the Kriebel and Dean’s convolution model (Kriebel and Dean, 1993) which predicts the beach profile response depending on wave breaking and water level variations due to storm surge. In addition, there are other models such as the PCR model (Ranasinghe *et al.*, 2011) which provides probabilistic estimates of coastal recession based on governing physical processes and offers more reliable estimates than the Bruun Rule.

For computing erosion at a greater resolution, process-based models, or in combination with parametric models, are recommended. These models can represent morphological changes due to sediment transport. Such models have been used to perform high-resolution sediment analysis to evaluate shoreline evolution around coastal protection works and inform coastal managers and decision-makers regarding the inclusion of natured-based solutions into coastal protection schemes. Similarly, the output of these detailed models can be used for the evaluation of multiple scenarios, as well as a sensitivity analysis of the longshore transport of sediment and coastline morphodynamics.

Impact and risk analysis

In order to translate hazard maps into impact information, quantitative information on a range of social, ecological and economic coastal impact indicators are required. Tools that incorporate this information supports users to explore the effect of climate change on coastal environments and societies; to explore the cost and benefits of coastal adaptation options; and to set priorities for international co-operation with respect to climate change and development, among others.

For regional and local impact assessments, several methods exist that can quantify both direct and indirect impacts. Direct impacts are assessed using detailed exposure, vulnerability and hazard information, and are conveyed as either monetary values or the number of affected entities. The monetary assessment is useful for long-term planning strategies, providing a basis for the choice of measures to develop community resilience to natural hazards through a cost-benefit analysis (section 5.1) (Kind et at., 2017). Additionally, information on the direct impact of the expected number of people affected is important for emergency response decisions.

To account for the indirect impacts of coastal hazards, methodologies have been proposed to include indicators such as household displacement, financial recovery of households and businesses, business supply chain disruption, ecosystem recovery, risk to life and utility and transport disruption. Tools that include these indicators can be used to compare and identify hotspots and risk at a regional level using multi-criteria analysis (MCA) (section 4.3) to improve allocation of resources, improve coastal management and increase the resilience of coastal areas. Other coastal management tools which provide a greater focus on ecosystem disruption often estimate the impact of hazards in the natural environment to identify climate change adaptation options for nature and ecosystems. Additionally, indirect impacts can be identified if critical infrastructure (CI) is analysed. Tools to identify the cascading effects from the failure of CI can be useful, since they can support cross-disciplinary collaboration and identify measures that can develop area resilience and robustness against natural hazards.

At the local level, the use of hazard and impact information can be important for the identification of climate adaptation tipping points. For example, predictions of changing hazard and risk can provide an indication of when it is suitable to intervene and which type of adaptation measure to implement. This is the so-called dynamic adaptation pathways (section 5.6), which can be used for coastal regions in order to adapt to uncertain SLR.

Assumptions

Assumptions and limitations of the described methods/tools are based on input data requirements of availability, quality and duration of time-series; simplifications within each model, of which some are only valid under specific conditions; and data available, including measurements and satellite imagery, to calibrate and validate each model. Limitations also apply to the scale and complexity of the analysis.

Model verification

Both hazard and impact models can be verified/validated through comparison with historical flooding events, for example, using gauge measurements, satellite data and high-water marks, and their reported consequences. Historical events are also associated with return periods[19] and model outputs for the same return period can be compared. Another option for validation is to model a specific historical event with the initial configuration of the model and, based on the results, calibrate the settings to match the response of the system.[20] For erosion hazard, model verification can be obtained by comparing historical shoreline/ dune movements using satellite imagery and maps. Impact models can be verified by comparing historical reported damages for a single event. An overview of current practice and possible improvements for validation of flood risk models can be found in Molinari *et al.* (2019).

Input data

In general, climate re-analysis datasets, such as ERA5, from global and regional circulation models are used in order to derive statistics for present-day climate extremes (section 1.2.2). Moreover, historical datasets can be used to develop synthetic conditions that can be used as an input to run probabilistic hazard assessments. On the other hand, scientifically accepted climate projections are needed to assess future hazard conditions under different scenarios. All models rely on bathymetry and/or topography data. Sources can be global datasets or locally derived Digital Elevation Models (DEMs). The resolution and vertical accuracy of the DEM will define the hazard maps.

In addition to hazard maps, impact and risk modelling also requires information on vulnerability and exposure. Exposure datasets need to consist of, for example, population data (density and distribution), location of assets, construction material, location of critical infrastructure and land use maps. Vulnerability information can be attained using damage functions (locally developed or global dataset), construction costs, main economic activities or sectors, annual income distribution, GDP maps and general information regarding hazard(s) impacts including activities interrupted, sickness outbreaks and inaccessible roads. Future socio-economic projections are required, such as Shared Socio-Economic Pathways (SSP's) (section 1.3.1) or local sources, in order to assess the future changes in exposure and vulnerability at the continental, regional or local scale. These changes can be related to GDP and populations estimates according to defined and accepted scenarios.

Outputs

The main outputs of hazard models are hazard maps indicating the extent, magnitude and probability of occurrence, while the main results of impact and risk models are the quantification of damages (economic: direct and indirect) and intangible assets

[19] However, the number of events available affect the return period trends. This can be addressed though through the generation of synthetic events.

[20] This approach can lead to the problem of equifinality, which can result in larger uncertainties associated with the model outcomes.

affected. Both models can be connected to explore the reduction in risk due to the implementation of different adaptation strategies. Ultimate decision making can utilise these outputs and perform multi-criteria analysis (section 4.3), cost benefit (section 5.1) and cost effectiveness analysis (section 5.2) in order to determine the most appropriate measure. These decision support systems compile the information and provide users with clear information regarding possible strategies.

At a European level, the RISC-KIT toolkit was used to identify areas of increased coastal risks, so-called hotspots. Hotspots were located using a combination of different hazard and exposure indicators. These hotspots were ranked using multicriteria analysis and the impacts for land uses and transport where calculated in addition to an estimation of daily disruption indicators. This was conducted for several locations across Europe. Results can be used by stakeholders to identify and prioritize locations where potential interventions or more in-depth studies are needed.

Strengths and weaknesses

	Method	Strengths	Weaknesses	Rapid Assess.
Flood hazard	**Static inundation approach**	Quick assessment of hotspots for flooding without need of high computational power - results can be used for a first hazard assessment, especially for large-scale applications. Expert modelers not required.	In low-lying areas, flooding could be overestimated. Results cannot be used to design local adaptation measures.	Yes
	Fast flooding solvers	Quick hazard assessment with increased accuracy. Can be used for probabilistic risk assessment and forecasting.	Running models often require expert input.	Yes
	Coastal hazard wheel	Dataset ready with 655 hazard evaluations for generic coastal environments. Appropriate for regional and national estimations.	Exact level of hazard reduction cannot be obtained for specific management options included in the tool.	Yes
	Physical process-based models	All physical mechanisms are included leading to high quality data. Suitable for small-scale applications. Results can be used for the identification of flooding hotspots and detailed design of measures.	Required modelling time and computational power is high. Application of model requires trained staff.	No
	Bruun Rule (SLR retreat)	Quick assessment of hotspots for erosion in sandy beaches due to SLR (continental scale).	Erosion can be overestimated due to the neglection of longshore transport.	Yes

Erosion hazard	**Kriebel Dean (storm retreat)**	Results can provide direct estimates of nourishment quantities which are useful for decision-makers.	Empirical model and therefore has limitations in its use.	Yes
	Prob. coastline recession model	Improved estimates of SLR retreat without increased computational time.	Requires long-term water level data and Monte Carlo simulation, requiring trained staff.	Yes
	Physical process-based models	Models can be used to observe the effect of adaptation strategies. All processes are included, and results can be used for detailed design of measures.	Required modelling time is high and needs trained staff.	No
Flood & erosion impact	**DIVA tool**	Integrated model that supports the generation of quantitative information for several socio-economic and climate indicators.	Cannot be used for detailed assessments.	Yes
	Flood impact assessment tool	Flexible tool for quantifying direct impacts.	Cannot quantify indirect impacts.	Yes
	INDRA	Accounts for indirect damages (disruptions).	Configuration can be detailed. Requires training and time.	No
	Circle tool	Interactive tool that supports and enhances stakeholder participation for the identification of cascading effects.	Cannot quantify the costs of cascading effects (indirect impacts).	Yes

Suitability for rapid assessment

See table above.

Research gaps

The DEM input is fundamental to flood hazard modelling and determines the accuracy of the final map. Therefore, the quality of analysis will increase with a higher accuracy of the DEM. The highest resolution is ~30m on a global scale and is freely available,[21] but the vertical accuracy is an issue especially when assessing flood hazard in coastal lowland areas (Vernimmen *et al.*, 2020). Often, higher resolution DEM's are available for national or local regions. Besides resolution considerations, factors such as completeness and vertical resolution of a dataset should be considered as well. Member States (MS) should base their assessments, maps and plans on appropriate 'best practice' and 'best available technologies' not entailing excessive costs in the field of flood risk management. Aside from this, there are no legal requirements from

[21] NASA Shuttle Radar Topography Mission, SRTM global 1-arcsecond: https://earthexplorer.usgs.gov/

the EU directive; this is implemented as a process directive and as such, legal requirements are focused on this. There is a reporting guidance, predominately focusing on that an MS should carefully describe the methods and data applied, however there is no requirement regarding what is needed for use. MSs do not use global DEMS for their assessments under FD and normally a finer resolution is used, however this can vary considerably between countries.

Another EU directive is INSPIRE,[22] which aims to create a European Union spatial data infrastructure for the purposes of EU environmental policies and policies or activities which may have an impact on the environment. This European Spatial Data Infrastructure will facilitate public access to spatial information across Europe and assist in policymaking across boundaries. INSPIRE sets out guidelines and data specifications for EU members regarding elevation datasets, hydrography, land cover, agricultural facilities, buildings, natural risk zones, oceanographic information, sea regions and population distribution and demography, among many other categories that can be useful for hazard and impact modelling.

Exposure is often represented by simplified land-use classes, especially in analyses on a broader scale (continental or global). This leads to an underrepresentation of heterogeneities in exposure. Including spatial assets, such as offered by Open Street Map, within an impact analysis supports modelling at a higher resolution. However, the completeness of such a database should be verified before applying.

Efforts have been made to capture the hydrodynamic processes in models to increase the accuracy of estimating floods. However, the physical processes forcing flooding are still topics of current research in order to improve existing models and, ultimately, policy forming concerning flood events. In addition, the quantification of damage and upscaling of vulnerability information is also needed through machine learning techniques to provide better estimates of the impacts produced by different types of hazards.

Finally, more research is needed for the accurate estimation of risk reduction measures and the effect of human behaviour in future risk estimation. Future risk estimation often considers that the current situation, such as land use and human distribution, will remain constant. Agent based modelling (section 4.1) can help to understand human decisions based on the risk that they are exposed to, and therefore better estimates can be obtained to improve cost-benefit analyses for decision-making. They can also provide key stakeholders a greater understanding of the system in order to establish future development plans and spatial planning policies.

[22] https://inspire.ec.europa.eu/

1.2 Techniques to derive extreme climate events

1.2.1 ETCCDI extreme climate indices

In order to support the assessment of changes in extreme climate events and provide a comprehensive overview of temperature and precipitation statistics, the Expert Team on Climate Change Detection and Indices (ETCCDI) defined a set of 27 climate indices that can be generated from daily climate data (Silliman *et al.*, 2013a, b). There is no unique definition of an extreme event, since it can describe either a characteristic of a climate variable or its impact (Stephenson, 2008).

An extreme (weather or climate) event is generally defined as the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends ('tails') of the range of observed values of that variable. The Fourth IPCC Assessment Report (IPCC, 2007) defines an extreme climatic event as one which is rare within its statistical reference distribution at a particular place and time. Definitions of "rare" vary, but an extreme weather event would normally be as rare as, or rarer than, the 10th or 90th percentile of the observed Probability Density Function (PDF). Extreme climate statistics must be taken into consideration in order to determine an extreme event, for instance, in Kharin *et al.* (2007) where 20-year return values of annual temperature and precipitation extremes are considered. The descriptive indices developed by ETCCDI represent a variety of extremes: "moderate extremes," which refer to events that occur multiple times per year, and "extreme extremes", which occur once (or less) per year (Herold *et al.*, 2017).

Climate indices used within the literature are frequently applied to climate hazard and risk assessments, as well as studies concerning climate adaptation challenges. These indices are considered as proxies for relevant hazards associated with climate moderate extremes, such as drought, heat and cold waves, floods, flash floods, landslides, soil erosion and water scarcity.

Users and application

End-users of these indices include:

	European	National	Local/Project
Policy and public decision-makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

The ETCCDI extreme climate indices support the adaptation policy cycle:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change

Table 3: Definitions of the 27 ETCCDI climate extremes indices. [23]

	Index	Description
1	**FD**	Number of frost days: Annual count of days when TN (daily minimum temperature) < 0°C
2	**SU**	Number of summer days: Annual count of days when TX (daily maximum temperature) > 25°C
3	**ID**	Number of icing days: Annual count of days when TX (daily maximum temperature) < 0°C
4	**TR**	Number of tropical nights: Annual count of days when TN (daily minimum temperature) > 20°C
5	**GSL**	Growing season length: Annual count between first span of at least 6 days with daily mean temperature T>5°C and first span with T<5°C
6	**TXx**	Monthly maximum value of daily maximum temperature
7	**TNx**	Monthly maximum value of daily minimum temperature
8	**TXn**	Monthly minimum value of daily maximum temperature
9	**TNn**	Monthly minimum value of daily minimum temperature
10	**TN10p**	Percentage of days when TN < 10th percentile
11	**TX10p**	Percentage of days when TX < 10th percentile
12	**TN90p**	Percentage of days when TN > 90th percentile
13	**TX90p**	Percentage of days when TX > 90th percentile
14	**WSDI**	Warm spell duration index: Annual count of days with at least 6 consecutive days when TX > 90th percentile
15	**CSDI**	Cold spell duration index: Annual count of days with at least 6 consecutive days when TN < 10th percentile
16	**DTR**	Daily temperature range: Monthly mean difference between TX and TN
17	**Rx1day**	Monthly maximum 1-day precipitation
18	**Rx5day**	Monthly maximum consecutive 5-day precipitation
19	**SDII**	Simple precipitation intensity index
20	**R10mm**	Annual count of days when PRCP≥ 10mm
21	**R20mm**	Annual count of days when PRCP≥ 20mm
22	**Rnnmm**	Annual count of days when PRCP≥ nnmm (nn is a user defined threshold)
23	**CDD**	Maximum length of dry spell: maximum number of consecutive days with RR < 1mm
24	**CWD**	Maximum length of wet spell: maximum number of consecutive days with RR ≥ 1mm
25	**R95pTOT**	Annual total PRCP when RR > 95p
26	**R99pTOT**	Annual total PRCP when RR > 99p
27	**PRCPTOT**	Annual total precipitation in wet days

The calculation of these indices supports the quantitative evaluation of the hazard level associated with weather and climate moderate extreme events and its potential variation as a consequence of climate change at the regional and local scales. They are calculated with respect to a reference period in a specific location (Christidis & Stott, 2016; Fioravanti *et al.*, 2016; Dosio & Fischer, 2018; Hong & Ying, 2018; Reder *et al.*, 2018). These hazard assessments, in conjunction with impact evaluations, can be used to inform risk assessment frameworks. By comparing index values evaluated for future climate projections with climate data related to a reference period, the calculation of the ETCCDI supports:

- assessing changes in the frequency or duration of future extremes of weather-induced processes such as landslides, floods, droughts, and heatwaves;
- evaluating potential impacts linked to changing patterns in temperature and precipitation;
- informing potential adaptation responses.

Depending on the considered spatial resolution (national, regional, local) and temporal scale (monthly forecast, seasonal forecast, decadal predictions or longer term projections), these indices can inform a range of policies and decisions: early warning systems such as urban heat health warnings (section 2.12); farming practices including planting species greater suited to the expected changing conditions in the next season, decade or longer term (section 2.2); and medium to long term

[23] http://etccdi.pacificclimate.org/list_27_indices.shtml

prevention, preparedness and management plans for extreme floods events (sections 1.1.5, 1.1.8, .1.1.10).

Calculating the ETCCDI indices supports the evaluation of characteristics of historic and future weather and climate moderate extremes, such as their frequency, amplitude and persistence (WMO, 2009). Observed data series provide data to generate index values for a historical/reference period, while simulated projected data derived from climatic models supports the potential identification of future climatic indices values. Comparing historical and future index values can support research predicting the potential impacts of climate change on different sectors and can therefore support the tailoring of adaptation strategies according to local conditions. For example, trends in the R95p index support the comparison of changes in demands on drainage and sewerage systems at different locations; trends in the indices of cold nights TN10p and warm days TX90p are relevant for comparing changes in heating and cooling demands (WMO-TD No.1500). The European Climate Assessment & Dataset (ECA&D) project further illustrates how the descriptive indices can be linked to the different impact themes defined by the Group on Earth Observations (GEO).[24]

Model and tool methodology

The indices of the ETCCDI are computed based on daily temperature values and precipitation volume (Klein-Tank *et al.*, 2009; Zhang *et al.*, 2011; Zwiers *et al.*, 2013). Climate data can be obtained from both observational datasets for historical and current periods, and from gridded data simulated by General Circulation Models (GCMs) and Regional Climate Models (RCMs) for historical, current, and future periods.

GCMs and RCMs: generating data which ETCDDI indices can be derived from

Future climate projections are predominately evaluated using GCMs which can simulate the response of the global climate system to external forcing. However, these models are generally unsuitable to simulate local climate since they are characterized by resolutions approximately, or coarser than, 100 km with only a few of the new generation CMIP6 models which can operate at a 25 km horizontal resolution.

RCMs, which dynamically downscale GCMs, are one of the most effective tools developed for providing high-resolution climate analyses and describing climate variability at a local scale of up to 2 km spatial resolution. Yet it is important to underline that RCMs are not a “zoom” of GCMs climate data: due to their higher resolution, RCMs have a greater ability to represent small-scale physical parameterizations, such as soil moisture-atmosphere interactions. They are also usually non-hydrostatic models in which they have an enhanced ability to incorporate vertical atmospheric movements which are often responsible for convective phenomena. Because these processes are incorporated into RCMs, they are often used to evaluate extremes, particularly when local scale assessments are required.

However, the propagation of uncertainties from GCMs promulgates to the associated RCM. These uncertainties can be grouped into three major categories: (i) scenario uncertainty, (ii) internal climate variability and (iii) model uncertainty (Hawkins and

[24] http://eca.knmi.nl/indicesextremes/

Sutton, 2009, 2011). As such, RCM results are strongly influenced by GCM performance and separating their respective performance abilities is therefore challenging. Nevertheless, it is expected that RCMs improve GCM results for analysis at the local scales. Yet, the performance of GCMs and RCMs are strictly dependent on the climate and geographical context under analysis, and subsequently the propagation of uncertainties or performances of the model adopted need to be carefully considered in relation to the specific context applied.

Any subsequent processing of GCM and RCM outputs, such as the calculation of climate indices and related anomalies, are therefore influenced by these uncertainties associated with climate models (Razavi *et al.*, 2016). As such, in order to generate the most reliable climate modelling outputs, an ensemble of climate models can be used to provide a mean from these models' outputs along with a distribution around this mean based on the outputs of each single model. This distribution provides the degrees of uncertainties associated with the ensemble mean. The use of multiple models, in conjunction with multiple datasets, provides the current best "safe side" approach (Herold *et al.*, 2017). While some uncertainties are shared by the different models within the ensemble, others are model-specific since they depend on the parameter configuration. Therefore, combining the outputs from an increasing number of models enables a greater realistic representation of the uncertainties. Yet, it is important to highlight that while this ensemble spread can provide important information regarding the range of plausible climate change, it is still incomplete (McSweeney and Jones, 2016).

Depending on the application, both GCMs and RCMs can be used for conducting index-based climate evaluations. For example, the Coupled Model Intercomparison Project (CMIP5) used a multi-model ensemble for a global scale ETCCDI evaluation in Silliman *et al.* (2013a, b), while index values obtained from climate data, simulated by RCMs, are most useful for local risk assessment and adaptation challenges. Since it provides more detailed information on the uncertainties (WMO, 2009), the combined use of different models is recommended for both GCMs and RCMs.

Generating ETCCDI indices

Different methodological approaches can subsequently be used to generate climate indices. Some indices are compared to fixed thresholds that do not change with respect to the site where the index is calculated. For example, the SU index (number of summer days) accounts for the annual count of days when TX (daily maximum temperature) is greater than 25°C. Some indices, such as the Rx1day index (daily precipitation volume) and the Rx5day index (monthly maximum consecutive five-day precipitation), adopt the maximum value recorded for the accounted month.

Other indices account for thresholds that vary between locations since they are expressions of anomalies relative to the local climate. In these cases, thresholds are typically defined as a percentile of the local data series relative to a specific time-period of at least 30 years in duration. Furthermore, some indices account for the duration, generally the number of days, of the phenomenon. For example, the Consecutive Dry Day (CDD) index identifies the maximum number of consecutive days with daily precipitation of less than 1mm, and the Consecutive Wet Day index identifies the maximum number of consecutive days with daily precipitation greater than 1mm. For the detailed definitions of each index, see table 3.

The 27 ETCCDI climate extreme indices are frequently used in literature for climate change impacts analysis and climate adaptation studies. For example, the analysis conducted for the development of the Italian National Adaptation Plan (currently under consultation) is based on the calculation of climate anomalies by accounting for some of the ETCCDI. The calculation of climate anomalies based on the proposed indices can provide a hazard assessment under current and expected future climate conditions and can subsequently support local risk assessments. However, the spatial scale of such analysis is dependent on the spatial resolution of the RCMs. Indices represent proxies for specific hazards, and they can be used for rapid hazard assessments by practitioners. For example, the R95p index identifies precipitation periods over the 95 percentiles which can support the rapid evaluation of the pluvial flood events. Similarly, the CDD (the maximum length of a dry spell with rainfall less than 1 mm) can be used for rapid assessment of drought events and their related impacts.

In table 4, a proposal of indices suitable for the evaluation of different hazardous events, including analysing their characteristics in relation to the duration and the intensity of extreme temperature and heavy rain events, is outlined. Specifically, the following hazards have been selected: rainstorms, cold waves, heatwaves, river floods, landslides and fires. For each of these hazards, a number of indices have been proposed which can support rapid hazard assessment. The indices can be applied to different sectoral contexts, such as tourism, health care and energy distribution, to evaluate the expected future variations in the hazard distribution under different climate scenarios. It is possible to combine some of these indices for a composite hazard/risk assessment and support the multi-hazard analyses. Several methods are available in the literature for combining and aggregating indices, such as additive and geometric techniques (OECD, 2008). By combining hazard indices with exposure and vulnerability analysis, which are generally supported by the definition of sectoral tailored indices, risk levels can be evaluated and accordingly classified. The study published by Mysiak *et al.* (2018) represents an example of an operative application of the risk assessment procedure conducted for the Italian territory based on a multi-indices approach.

To support interested end-users, specific software packages, which operate for both Microsoft Windows and Unix/Linux, have been developed. The developed packages are based on the freely available statistical package, R, which supports: i) data homogenization such as HtestsV4 and ii) indices calculation: RClimDex and its variants, for example, FclimDex and CLIMDEX.PCIC.[25]

Assumptions

The definition of the ETCCDI indices is based on the main assumption that climate change causes variation in the intensity and frequency of moderate extreme events and that these changes are expected to increase by the end of the twenty-first century (IPCC, 2013). The usage of such indices for the identification of potential future

[25] http://etccdi.pacificclimate.org/software.shtml

changes in spatial and temporal patterns of climate variables (temperature and precipitation) is based on the assumption that the required inputs from a combination of observational and modelled data series are able to represent moderate extremes under different future temperature scenarios (Lewis *et al.*, 2019).

Table 4: Potential hazardous events and related ETCCDI suitable for supporting hazard analysis.

Hazardous Event	Indicator Definition and Unit of Measurement	Acronym	Unit of Measurement
RAIN STORM	**PRCPTOT (mm):** total precipitation - precipitation sum in wet days (days with precipitation greater than or equal to 1 mm)	PRCPOTOT	mm
	SDII (mm/wet day): simple precipitation intensity index	SDII	mm/wet day
	RX1DAY (mm): maximum 1-day precipitation amount	RX1DAY	mm
	RX5DAY (mm): maximum consecutive 5-day precipitation amount	RX5DAY	mm
	R10 (days): number of heavy precipitation days - number of days with precipitation greater than or equal to 10 mm	R10	days
	R20 (days): number of very heavy precipitation days - number of days with precipitation greater than or equal to 20 mm	R20	days
WINTER TEMPERATURE DECREASING	**TNN (°C)**: minimun value of daily minimum temperature	TNN	°C
	TNX (°C): maximun value of daily minimum temperature	TNX	°C
	ID (days): number of Ice Days (TX<0°C)	ID	days
SUMMER TEMPERATURE INCREASING	**TXX (°C)**: maximun value of daily maximum temperature	TXX	°C
	TXN (°C): minimun value of daily maximum temperature	TXN	°C
COLD WAVE	**CSDI (days):** Cold Spell Duration Index - total number of days per period (annual or seasonal) in which the minimum temperature is less than the 10th percentile of the minimum temperature in intervals of at least 6 consecutive days for the reference period (1971-2000)	CSDI	days
	CFD (days): Consecutive Frost Days - maximum number of consecutive days with minimum temperature less than 0°C	CFD	days
	ID (days): Number of Ice Days (TX<0°C)	ID	days
HEAT WAVE	**TX99p (days):** Very warm day-times (days) - Days with Tx>99th percentile of daily maximum temperature calculated for a 5 day window centred on each calendar day of the reference period (1971-2000)	TX99p	days
	WSDI (days): Warm Spell Duration Index - total number of days per period (annual or seasonal) in which the maximum temperature is greater than the 90th percentile of the maximum temperature in intervals of at least 6 consecutive days for the reference period (1971-2000)	WSDI	days
RIVER FLOOD and LANDSLIDES	**PRCPTOT (mm):** Total Precipitation - precipitation sum in wet days (days with precipitation greater than or equal to 1 mm)	PRCPTOT	mm
	SDII (mm/wet day): simple pricipitation intensity index	SDII	mm/wet day
	RX1DAY (mm): maximum 1-day precipitation amount	RX1DAY	mm
	RX5DAY (mm): maximum consecutive 5-day precipitation amount	RX5DAY	mm
	R10 (days): number of heavy precipitation days - number of days with precipitation greater than or equal to 10 mm.	R10	days
	R20 (days): number of very heavy precipitation days - number of days with precipitation greater than or equal to 20 mm	R20	days
FOREST and LAND FIRE	**HW (days):** Hot Waves - number of days with maximum temperature greater than 35°C	HW	days
	WD (days): number of Warm (Tg>75th percentile) - Dry (Pr≤25th percentile) days	WD	days

Input data

The calculation of ETCCDI is based on daily temperature and precipitation time series data, which can be derived from both observational and simulated data. For statistical reasons, observational data series for the analysis of the historic extremes should be continuous and quality-controlled with a duration of at least 20 years in order to estimate the frequency and the intensity of events with a high return period.

Furthermore, it is necessary for data series to contain a sufficiently high time resolution of at least one acquisition per day in order to support the evaluation of the extreme monthly variability. In addition to observational datasets, gridded data simulated by General Circulation Models (GCMs) and Regional Climate Models (RCMs) could also be used to calculate temperature and precipitation indices over a defined study area for both historical and future periods.

The Copernicus' C3S program[26] provides users access to climate data free of charge and without restrictions. Within this, a catalogue of daily and monthly-resolution RCM data based on multiple experiments, models and time periods across Europe are available through the Coordinated Regional Climate Downscaling Experiment (CORDEX). Data can be downloaded for a specific location and time period in order to calculate the ETCCDI climate indices. Furthermore, the program supports the development of tailored applications for post-processing of the data, including the calculation of specific indices.[27] EURO- CORDEX, the specific name of the European branch of the international CORDEX initiative providing climate data across Europe, has data available on the CDS which covers from 1950 to 2100 with a spatial resolution of approximately 12 km and a temporal resolution including 3h, 6h, daily, monthly and seasonal data.

Alternative data suitable for ETCCDI index calculations are the ERA5 dataset that provides hourly estimates of a significant number of atmospheric, land and oceanic climate variables with a resolution of 30 km. ERA5 replaces the ERA-Interim reanalysis that stopped being produced on 31 August 2019. The entire ERA5 dataset from 1950 to present is expected to be available for use in 2020 on C3S.

The E-OBS observational datasets[28] (Haylock *et al.*, 2008) could also be used as a reference for the index calculation for the historical-present period, as has been applied within several studies (for example Dosio, 2016). They include daily temperature and precipitation observations from 1950 to 2006, interpolated to a regular grid with a resolution of around 25 km across the entire European land area.

Outputs

Extremes analyses conducted through the calculation of ETCCDI indices can be provided in the form of both numerical values and maps. These outputs can support climate policymaking at the local and national scales, and decision-makers and local authorities can use these as an input for climate change impact assessments to support to adaptation planning.

The ETCCDI indices were integral to the development of the guidelines on "Analysis of extremes in a changing climate in support of informed decisions for adaptation" provided by the World Meteorological Organization (WMO) in 2009. Given that climate adaptation strategies should account for future climate projections in order to evaluate changes in intensity and frequency of future extremes events, the proposed guidelines

[26] https://climate.copernicus.eu/climate-datasets
[27] https://cds.climate.copernicus.eu/cdsapp#!/software/app-health-heat-waves-projections?tab=app
[28] https://www.ecad.eu/download/ensembles/download.php#datafiles.

are aimed at including changing climate conditions in the assessment and estimation of weather and climate moderate extremes.

ETCCDI can also be used as a support tool in the development or revision of national adaptation strategies and plans. For example, in 2011 the Council of Ministers of Luxembourg adopted a National Adaptation Strategy, which was a framework for informing policymakers and addressing climate adaptation impacts (EC, 2018).

A recent application of the ETCCDI can be found in Mysiak *et al.* (2018), where a Climate Risk Index for Italy was proposed to support national authorities in designing adaptation policies and plans. The proposed methodology is based on the evaluation of anomalies of selected indices for assessing climate change-amplified hazards. Specifically, in this study, nine indices were calculated using the simulated daily weather variables: (i) maximum near-surface air temperature (TX); (ii) minimum near-surface air temperature (TN); and (iii) near-surface precipitation (PR). The proposed approach can produce climate risk-related rankings of subnational administrative units, providing an initial basis for local adaptation plans.

Some extreme climate indices are also included in the Portuguese climate portal,[29] which provides information on climate scenarios at the NUT3 (Nomenclature of Territorial Units) level for a range of indicators and on climate change vulnerabilities and risks in Portugal. The web portal was developed and used to support the revision of the country's National Adaptation Strategy (EEA, 2018). Similarly, Latvia also included extreme climate indices in their risk and vulnerability assessments, carried out for the development of their climate adaptation strategy and action plan (EEA, 2018).

Extreme climate indices were also applied in a sectoral vulnerability analysis to support adaptation policy development for three pilot river basins in Turkey. The study was undertaken in the framework of the 'Climate Changes Impact on Water Resources' national project,[30] aiming to identify the impacts of climate change on surface and ground waters and to define relevant adaptation activities (EEA, 2018).

Strengths and weaknesses

Strengths	Weaknesses
Supports the identification of changes in weather and climate moderate extreme event patterns and distributions detectable at a local scale.	Uncertainties associated with climate models, primarily due to different emission scenarios, model parameterization and dataset reliability.
Can provide a rapid assessment of climate change impacts with respect to temperature and precipitation.	The indices do not support estimations regarding the occurrence of events in relation to their return periods and, for

[29] www.portaldoclima.pt
[30] http://iklim.ormansu.gov.tr/Eng/

	this reason, they do not provide the spatial distribution of potentially affected areas with the same accuracy of statistical approaches and simulation models.
The calculation of climate anomalies based on the proposed indices can support studies of hazard and risk assessment for a specific location.	Existing RCM bias prevent the direct use of the climate models outputs as inputs for impact models, and therefore this bias needs to be addressed in order to improve their applicability.

Suitability for rapid assessment

The indices can be used as a support tool in the rapid analysis and assessment of risk since they provide information regarding the changing hazard level due to variation in temperature and precipitation patterns. These can subsequently inform hazard variation without running specific hazard models, which require high computational effort and ancillary information for calibration.

Research gaps

At present, ETCCDI indices only account for temperature and precipitation data, yet future applications should also include other climate and weather parameters such as wind, snow and humidity.

Further, the current ETCCDI indices do not account for compound events. This gap could be bridged by including a number of additional indices specifically devoted to evaluating different climate-weather moderate and extreme events which could be used in hazard assessments while tailoring the analysis to specific local requirements. For example, hazard analyses supported by ETCCDI could be integrated with those indices proposed in the framework of the European Climate Assessment & Dataset project (ECA&D), whose calculations account for data related to wind, sunshine, rain and snow precipitation, temperature, cloudiness, radiation and pressure.

Finally, there are currently relatively few ETCCDI indices available within the CDS web-applications.[31] It is expected that the number of indices will increase though with the development of new applications; already under development is a tool specifically devoted to the analysis of the occurrence and impacts of heavy precipitation events at the European level based on a number of ETCCDI indices (Service Contract n. 430 – on-going).

[31] https://cds.climate.copernicus.eu/#!/home

1.2.2 Extreme value analysis

Extreme value analysis (EVA) is a statistical tool used to estimate the likelihood of occurrence of extreme values based on several underlying assumptions in addition to observed or measured data for extreme climate or weather events.

Users and application

End users of EVA are:

	European	National	Local/Project
Policy and public decision makers	x	x	
Investment, finance and insurance.	x	x	x
Business and industry (private sector).			x
Research	x	x	x
Civil society and NGOs.			x

These models can be applied to assess various stages of adaptation policy and decision making:

- Stage 2: Assessing risks and vulnerability to climate change
- Stage 4: Assessing adaptation options

EVA can be used in several climatological, hydrological and other environmental decision-making scenarios where the likelihood of occurrence of extreme events is paramount to consider. The key challenge for EVA is to generate reliable estimates on the occurrence of extremes that have not, or only seldomly been observed, in the past. This requires extrapolations to minimum or maximum values based on reasonable assumptions on the distribution of extreme values. With this, the problem of limited availability of observations over time can be overcome. The use of EVA has been widely applied to the univariate case, yet when considering multivariate or bivariate extremes, such as compound events, the mathematical theory of EVA is a relatively novel field (Karpa, 2015). In bivariate analysis is more common to use copula theory or bayesian networks to determine joint probabilities. Notheless, previous studies have used the average conditional exceedance rate (ACER) method to account for bivariate situations and have demonstrated accurate estimates of the bivariate extreme value distribution when applied to time series of wind speed and wave height (Karpa, 2015).

EVA can be used to estimate the frequency (return periods) of extreme events, which often serve as design values for, for example, flood protection infrastructure which occur with a given probability given past observations, uncertainties, changes and trends herein, or changes projected by climate models for a perturbed climate. It is also possible to identify environmental covariates that drive extremes or assess the likelihood of temporal changes in an extreme event. Information derived from this statistical tool can be used as an input in hazard and impact models to understand the risks of a changing climate/ weather on people, ecosystems and infrastructure. Moreover, this information can be used for the definition/ modification of safety standards and building codes to increase climate resilience within future developments and infrastructure interventions.

Model and tool methodology

Annual maxima method (AM)

Extreme value theory is commonly used for predicting extreme events' maximum and minimum values. Several approaches exist for conducting EVA. The most traditional approach is based on the "three types theorem" (Fisher and Tipper, 1928) and the Gumbel studies (1958) which states that under certain conditions, the distribution of standardized maxima converges to one of the three limiting distributions: Gumbel (Type I), Frechet (Type II), and Weibull (Type III). The combination of the three families is called the Generalized Extreme Value (GEV) distribution which has three parameters: location, scale and shape that define the behaviour of the tail/ distribution of extreme values. If the GEV distribution is used for determining the probability of greater extreme events than those previously observed, the observed data is divided into blocks of equal size (non-overlapping periods), therefore restricting the attention to the maximum observation in each period. Since the time series available in climate analysis typically spans only a few decades, the annual maxima are usually low which leads to high uncertainty of return values calculated with this methodology. This described methodology is usually known as the "Annual Maxima (AM)" or the "block maxima" method.

This constitutes the simplest EVA method and is usually recommended when the only available information is block maxima, for example yearly maxima, or when observations are not exactly independent and identically distributed. For example, there may be a seasonal periodicity in case of yearly maxima or a short-range dependence that is significant within, but not between, blocks.

A GEV distribution for minima/ lower tail also exists, which implies a change in sign in the formulation of the distribution. Normally the use of GEV for minima is commonly used for modelling system failure but can also be used for climate extreme such as drought and low precipitation.

r-largest order statistics approach

An extension of the AM method is the *r*-largest order statistics approach, which can use a greater range of information from observational data than solely the block maxima. This method extends the GEV distribution and estimates the GEV parameters when the *r* largest values are available for each block. This method improves the precision of the standard AM analysis, since it includes additional information; nonetheless, if a block happens to contain a greater quantity of extreme events than another, then it is preferred to avoid any blocking.

The choice of the r value is critical for the EVA. Methodologies to select the *r* value have been studied by Bader *et al.* (2016) and have been incorporated successfully within the open access, EVA package R-codes which implements the r-largest order statistics model and provides data generation, fitting and return levels as well as sequential tests (goodness of fit tests) for the choice of the r-value in the model. The r value should be low relative to the block size to avoid bias however, the value should not be too low since the variance of the estimator can be high. The methodology has been applied to hydrology and coastal, wind and corrosion engineering.

Peaks-over-threshold method (POT)

The POT method is based on the Generalized Pareto Distribution (GPD), another frequently used distribution to model tails/ extreme values. The main concept of the method is to use a threshold to seclude values considered extreme to the rest of the data and create a model (in this case, the GPD) for the extreme values by modelling the tail of all the values that exceeds this threshold. The approach consists of fitting the GPD to the peaks of clustered observations exceeding a selected threshold (see Pickands, 1971 and 1975, and Davidson and Smith, 1990). The GPD has two parameters, scale and shape, that are similar to those within the GEV distribution of the block maxima method. The POT method has proven to innately contain greater flexibility than the AM approach, given that it can account for tail asymmetries (McNail and Frey, 2000) and all significantly large observation values within a sample.

An important choice within the POT method is the selection of the threshold value, which requires a trade-off between bias and variance. This is the same for the r-largest order statistics model. Rydman, 2018, discusses several methods to select an appropriate threshold value.

The "peaks over threshold" (POT) method has been considered to supply greater accurate estimates of the parameters and quantiles of the extremes than the other methods presented regarding the extreme tails (Katz *et al.*, 2002). This approach has been recommended by the IPCC (2002 workshop on changes in Extreme Weather and Climate Events) in place of the AM method.

Non-stationarity

The AM and POT models were derived based on the assumption that the underlying process being studied consist of a sequence of independent and random variables. This is not always the case as the climate cannot be considered stationary due to, for example, seasonal effects, climate patterns and long-term trends. Sometimes declustering methods can be used in order to filter dependent observations to obtain threshold excesses that are still approximately independent.

In other cases, it is possible to incorporate the dependent behaviour into the parameters of the chosen distribution by expressing those model parameters as a function of time. For example, in a GEV distribution it is common to express the location parameter as a linear function of time when studying maximum sea levels. Often, only the location and scale parameters are expressed as a function of time using either linear, quadratic, exponential or change-point models, among others. The shape parameter normally presents a greater challenge to estimate with precision, therefore in the POT method, specifying a model with different parameters for each season is usually applied.

A different situation occurs when managing variables that are related to another dataset. This is often referred as a covariate variable. When incorporating this type of data, the parameters are expressed as an inverse-link function, as explained by Coles (2004).

Point process approach

An alternative method to modelling extreme values uses the theory of point processes. This approach provides an interpretation of extreme value behaviour that enables a greater natural formulation of non-stationarity in threshold excesses than those obtained from the generalized pareto model.

This approach supports modelling both the frequency of exceeding a high threshold and the values of the excesses above it. The method was first developed probabilistically by Leadbetter, Lindgren, and Rootzén (1983) and Resnick (1987), and as a statistical technique by Smith (1989) and Davison and Smith (1990).

Estimation of parameters

There are several techniques to estimate the parameters of extreme value models. Some of them include graphical methods based on probability plots such as the quantile-quantile (Q-Q) plot; which has been used widely to explore data and to conduct fitness tests, or the Probability Plot Correlation Coefficient (PPCC) which has been proved to be a simple and powerful method (Booji, 2002). Other methods include moment-based techniques, including method of moments, method of Probability Weighted Moments (PWM) and L-moments. These techniques equate functions of model moments with their empirical equivalents to obtain explicit expressions for the estimated parameters.

In addition, likelihood-based methods, which require solving non-linear systems of equations such as Bayesian and Generalized Maximum Likelihood estimations (GMLE/MLE), are methods which estimate the parameters as specified functions of order statistics. This method can also account for non-stationarity and, while each technique has its advantages and disadvantages, the utility and adaptability of the likelihood-based technique promotes it as the widest applied approach. Nonetheless if this method is used, for example, in conjunction with the GEV approach, it can be challenging to not alter the asymptotic properties of the Maximum likelihood estimator (MLE). According to Smith (1985), when the shape parameter of the GEV is greater than -0.5, the MLE conserves the usual asymptotic properties. For any value lower than -0.5 (short bounder upper tail distribution), the properties are altered and therefore other methods are recommended such as position weight matrix (PWM).

Normally, the choice of the technique to estimate the distribution parameters depends of the Extreme Value form applied. For example, the Poisson-GPD model requires the use of likelihood-based methods (El-Jabi, 1998; Smith, 2001). For data generated by GCMs and RCMs, the same approach is usually indicated (Smith, 2001). Moment-based techniques are preferably applied when using small sample sizes (Kharin and Zwiers, 2000) and they are used frequently with block maxima models (Kysely, 2002).

Assumptions

The most important assumption for both the GEV and GPD methods is that the random variable or process being studied needs to be independent and stationary, although the extreme value theory maintains validity under some forms of general dependence and non-stationary conditions. In addition, depending on which technique is being used to estimate the distribution parameter, certain properties need to be respected, such as the asymptotic properties in MLE.

Limitations of the extreme value theory are also based on the availability, quality and duration of time series and frequency of measurements of the input data, as well as the capacity to check the models' validity.

Model verification

In order to verify the validity of an extrapolation based on one of the models used for extreme value analysis, it is common to conduct an assessment with reference to observational data. For this purpose, the probability, quantiles and return level plots are often used, which are methods based on a comparison of model-based and empirical estimates of the distribution function. In addition, a comparison can be made between the probability density function of a fitted model with a histogram of the data using the AM method, or a histogram of the threshold exceedances using the POT method.

Input data

In general, to perform a reliable statistical analysis, the sample of the variable under investigation should have enough data to be able to draw significant conclusions. The larger the sample, the greater the robustness of the statistical results. The minimum sample size depends, among other factors, on the probability models used and the type of tests applied. Methods to calculate this are proposed by Cai and Hames (2010), Shieh (2000), Sedit and Mauritsen (1988) and Vuckel and Doksum (2001), among others. There is no certain rule of thumb to determine the sample size, although a flat rule of thumb often indicates 30 as a popular minimum number of a sample size. Nevertheless, this approach is not recommended as a strict guideline and is better to perform a more detailed analysis using for example the asymptotic distribution of maximum likelihood estimators (MLE) (Cai and Hames, 2010).

Depending on the extreme analysis method conducted, whether Annual Maxima, r-largest approach or peaks-over-threshold, the initial sample size should be post processed through selecting the specific data used for the analysis of extremes. This will vary depending on the method, either through selecting: the maximum/minimum value; all values above/below a threshold; or a certain number of values determined by x-largest/smallest per time frame analysed. However, it is common practice to contain at least one value per time frame analysed, which could be in years, months or days.

In addition, it is important to know the initial quality of the datasets. The most important properties of a good dataset are that it is homogeneous, values are accurate, it covers a long-enough period to serve as a basis for the analysis, each period (month, season) in the data is represented equally well and that it doesn't contain faulty or unrealistic data. According to Caires and van Gent (2011), three quality checks should always be considered:

- homogeneity - check if there were changes implemented during the measuring and modelling or identify jumps and non-physical trends and remove these
- data coverage - check if the measuring device has failed to register data
- identification and removal of outliers - values that deviate abnormally from the mean.

As previously discussed, is important that the data input for extreme analysis is independent. Therefore, the sample used for analysis must be extracted in such way as to make this assumption realistic (see process of declustering in the methods section).

Unprocessed data input for statistical analysis can be found using hydro-meteorological offices' records for each country, or in open data sources such as the National Data Buoy Center (NDBC). Reanalysis data sources include ERA5, Copernicus Services datasets including the Marine Environment Monitoring Service, and the Metocean Data Portal (at the Danish Hydrological Institute), which can be used to download time series, among others. In general, the ideal dataset for conducting EVA depends greatly on the variable being studied. For some applications as rainfall analysis, daily data might not be enough and hourly or 15-minute data is desirable to capture high intensity peaks. For other applications, such as heat waves, daily data may be sufficient.

Outputs

Multiple software programmes are available to perform EVA, such as the ExtRemes Toolkit, which is an interactive program for analysing extreme value data using the R statistics programming language. The tool supports the analysis of the different methods of annual maxima, r-largest order statistics mode, peak-over-thresholds and point process approach, and can be used to obtain the probabilities associated with extreme values and the frequency of extremes. This tool can also be used to analyse extremes of dependent and / or nonstationary sequences.

Similar tools also exist such as the EVA toolbox from DHI, which includes a tool to extract extreme value series and an analysis tool that can test for independence and homogeneity of the input series for EVA, goodness-of-fit statistics, uncertainty calculations associated to quantile estimates and the evaluation of return periods. In addition, tools such as ORCA (Deltares) include in its functionalities a section on data validation to evaluate the appropriateness of the dataset and also include already automated methods for the collection of EV data using either the AM method or POT method, including the calculation of the optimal threshold. Other similar tools for extreme value analysis include WAFO (NTNU and Lund University), EVIM (University of Windsor and Bilkent University), EXTREMES (MISTIS team at INRIA Rhone-Alpes), EVA (Stephenson and Gilleland, 2005; Guilleland *et al.*, 2012) and extreme (Roodman, 2017).

Other tools such as the Deltares Atlas of Metocean Conditions and the Metocean Data Portal (DHI) already provide extreme value analysis for some locations for variables such as wind speed or significant wave height return period values. These results can be downloaded as an input for hazard modelling. Similarly, European datasets of extreme events can be found on the JRC Data Catalogue, such as LISCOAST, which provides extreme values related to variables which can trigger a natural hazard, such as sea levels or storm surge, and are associated to a specific return period.

Relevant applications of extreme value analysis connected to decision making often includes extreme events as hazard drivers. This is used in combination with exposure and vulnerability data in order to evaluate the impacts of changing weather. The most relevant example of this was the LISCoAsT (Large-Scale Integrated Sea-level and Coastal Assessment Tool) dataset, which used the POT approach to compute extreme storm surge levels and extreme sea levels at the European level for the historical data and for future climate projections RCP 4.5 and RCP 8.5. The results showed that the average relative sea level rise (RSLR) across Europe is projected around 24 cm by 2050 and 77cm by 2100 under RCP 8.5, and that this dominates rising extreme sea levels especially under RCP 8.5. Averaged over Europe, the ratio of change in episodic extreme in waves and storm surges to RSLR ranges between 16% (2050) and 7% (2100) under RCP 8.5, however values can differ greatly for certain regions as, for example, the Baltic sea has projected values of up to 35% of RSLR by 2100.

The LISCoAsT project highlighted that rising seas will affect future losses from coastal flooding. The results demonstrated that, given the extreme value estimates, unprecedented flood risk will occur unless timely adaptation measures are adopted. This implies that even under moderate emission mitigation policies of RCP 4.5, coastal adaptation and protection measures should constitute a high priority in the European policy agenda, given that many regions are expected to experience the combined effect of Relative Sea Level Rise, raising water levels in excess of one meter by the end of the century. For many places, this level exceeds the limits of most present coastal protection measures. The findings further demonstrate that for many European coastal locations, the projected increase in extreme SSL could be approximately 15% but could reach 40% of the projected RSLR, implying that the combined effect could create significant consequences (Vousdoukas *et al.*, 2016).

Strengths and weaknesses

Method	Strengths	Weaknesses
AM	Simple model. This method removes the dependence with block size. Can be adjusted to account for non-stationarity (GEV parameter changing over time following covariates).	AM can exclude some large values such as the second highest per block. Must pick the block size which cannot be too large since data is lost and cannot be too small as extreme value theory would no longer apply.
r-largest	This method improves the	Issues can arise if a block happens

order statistics	precision of the standard AM analysis given that it includes a greater quantity of information from the data.	to contain a greater number of extreme events than others. The choice of the r value is critical for the EVA: r should be small relative to the block size to avoid bias, but it also cannot be too small since the variance of the estimator can be high.
POT	Retains all large values in the analysis. Can be adjusted to account for non-stationarity. However, techniques with greater complexity than with AM, such as declustering techniques, are required.	The method manages with dependence within block. Setting the threshold can be challenging as this cannot be too high since variance will increase and cannot be too low since this will result in bias.
Point process approach	This approach provides an interpretation of extreme value behaviour that unifies these other models, enabling a greater natural formulation of non-stationarity. The methodology approach supports modelling of both the frequency of extremes and their intensity.	When there is natural clustering in the variable, this approach is not recommended. The method can be complex and requires technical skills in order to interpret the results.

Suitability for rapid assessment

These methods are not suitable for rapid assessment due to the implementation of the methodologies and the interpretation of the results require in depth knowledge of statistical and probability analysis, and knowledge regarding the physical variable or process under review.

Software packages such as ExtRemes Toolkit and the EVA toolbox from DHI provide a computationally efficient tool for rapid assessment, however the tools also require profound technical knowledge for its application.

Alternatively, published datasets, such as JRC LISCoAsT, could provide outputs for policy-makers and stakeholders to support prioritisation of investments, use information to bridge hazard and risk estimates to provide an overview of the potential impact of extreme events or modify building and safety standard codes to establish that in hotspot zones for new infrastructure and adaptation/ refurbishment of old infrastructure.

Research gaps

A significant data gap includes high-quality and reliable historical climate records at a high resolution of either daily or hourly data. Some RCMs produce up to three-hourly data at a spatial scale of 10km, however there are no high-quality observations at the same resolution able to asses and evaluate those RCMs. Additionally, the hydrological and oceanographical measurement network is not complete.

There are issues regarding the homogeneity of existing datasets, especially for high resolution daily time series. In addition, further research is required to optimise the efficient use of the existing available data.

Further research and improvement on EVA methodologies are required in order to address issues such as: how to choose the threshold in a POT analysis?; what is the most suitable spatial/regional and multivariate model to estimate probabilities of climate extremes?; what is the best method to manage covariates? and to what extent may results of extreme value models be biased due to violated assumption of extreme value theory?

1.2.3 Changes in spatio-temporal patterns

The detection and assessment of climatic changes on a regional scale support the development and implementation of appropriate mitigation and adaptation measures. The accurate identification of climate change patterns, in particular changes in trends and cyclical patterns of extreme conditions of climatic fields, such as temperature and rainfall, is a key issue. To this aim different statistical approaches for detecting spatio-temporal patterns of regional climate change have been developed to perform attribution studies and to investigate potential changes from the seasonal to the centennial time scales.

Users and application

End-users of these indices include:

	European	National	Local/Project
Policy and public decision-makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.			

The tools developed for spatio-temporal pattern analysis support the adaptation policy cycle at:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change.

The application of these tools supports the evaluation of temporal and spatial changes in the hazard level associated to climate extreme events, using quantitative methods to assess and monitor changes in climate extremes with respect to a reference period. They support the evaluation of the variation of frequency and intensity of weather-induced processes such as landslides, floods, droughts, heatwaves and extreme heat disease. They can also be used for the evaluation of climate model simulations of both historic extreme events and future changes under different potential emission scenarios.

The results can be used to determine the levels of vulnerability at the local scale by providing insights into the investigated indexes at the intra city scale (Inostrosa *et al.*, 2016) and inform hazard assessments and subsequent impact evaluations, which are fundamental requirements for a risk assessment framework. For example, the identification of regions significantly affected by reduced precipitation can support the development of adaptation strategies such as local water metering and differential charging to incentivize water consumption efficiency.

In many economic sectors, adaptation to extreme weather has developed into an integral part of many planning processes. Current energy and transport infrastructure, for example, have developed considerable resilience to extreme precipitation and resulting flooding. In part, this has been a commercial or operational response to the experience of historic extreme events, and partially the requirement to incorporate resilience planning.

When planning adaptation strategies, the frequency and severity of extreme events are significant considerations. Yet, it is important to understand whether future climate will emulate historical trends or whether the frequency and/or severity of extreme events will accelerate. Depending on the spatial and temporal scale and resolution (monthly forecast, seasonal forecast, decadal predictions or longer term projections), these tools can support a range of policies and decision making: early warning systems such as Heat Warning Systems (IPCC 2012) which constitutes a health alert in cities (section 2.12); farming practices including planting crop species greater suited to expected changing climatic conditions for the next season, decade or longer term (section 2.2); medium to long-term flood prevention, preparedness and management plans (sections 1.1.5, 1.1.8 and 1.1.10), and subsequently instigates anticipatory action plans for health care systems (section 2.13) (WHO, 2007). The European Network of Meteorological Services created Meteoalarm as a system to coordinate and differentiate warnings across regions (Bartzokas *et al.*, 2010). There are a range of approaches which can be used to trigger alerts and subsequent response measures. A variety of agencies may be responsible for such alert systems, including emergency management departments and public health-related agencies (McCormick, 2010).

Model and tool methodology

The statistical distribution of climate data is significant for both the construction and validation of climate models, as well as for the investigation of the relative temporal changes. The assessment of both GCMs' and RCMs' abilities to represent observed spatial patterns of extreme events are based on statistical approaches such as spatial pattern correlations and multifractal cross-correlation analysis (MF-DXA). The pattern correlation is a measure of consistency in the spatial distribution of two variables, such as on an observational and modelled map. The two different maps can illustrate, for example, different times, different levels on a vertical plane or for depicting forecast and observed values. The anomaly correlation is a special case of pattern correlation. Pattern correlations can be computed directly (uncentered) or by computing anomalies from a central mean (centred). For diagnostic studies, such as Taylor diagrams, the centred pattern correlation is most commonly used. However, as discussed in the IPCC Third Assessment Report: *Climate Change 2001*, the centred pattern correlation should not be used for climate change attribution. Taylor diagrams (Taylor *et al.*, 2001) instead provide a statistical summary of the degree of similarity between patterns, for instance, between observed and modelled extreme temperature values across Europe. Additional information, such as percentage bias, can also be added to the conventional Taylor diagram.

The detection, estimation and prediction of trends and associated statistically and physically significant changes are important aspects of climate research. For example, given a time series of temperature extremes, such as the 99th percentile of the daily precipitation distribution in a decade, the trend is the rate at which the 99th percentile of temperature changes over an extended period of time. This trend may be linear or non-linear. Simple linear regression, through use of a Student-t test, is most commonly used to estimate the statistical significance of a linear trend. The non-parametric distribution free Mann-Kendall (M-K) test can also be used to assess monotonic significance of both linear and non-linear trends. Other tests, such as the Spearman's Rho test and Sen's T test, can also be used.

It is also important to deconstruct the temporal variability observed in climatic series using statistical methods for the extraction of trend, seasonal, and cycle components. Extreme Value Theory (EVT) (Coles *et al.*, 2001) and Empirical Orthogonal Function (EOF) (Zhang and Moore, 2014) analyses can be used to study possible spatial patterns of extreme events variability and how they change with time.

Based on the assumption that climate change is causing variation in intensity and frequency of extreme events, the described tools support:

- obtaining useful information for the evaluation of impacts under different climate conditions.
- informing potential adaptation responses.

Input data

Time series used for these analyses can be derived from direct observational data for an explicit time span and/or from simulated data which can be generated for both historical and future time periods. Additionally, reanalysis data from GCMs or RCMs can be used to simulate historical climate, integrating both spatial and temporal observational data available across a region.

Future climate projections are usually derived using GCMs, which can simulate the response of the global climate system to external forcing. However, these models are generally unsuitable to simulate localised climate since they are characterized by resolutions approximately, or greater than, 100 km, with only a few of the new generation CMIP6 models attaining a 25 km horizontal resolution. One of the most effective tools developed for providing high-resolution climate analysis through dynamical downscaling are RCMs, which can provide an accurate description of climate variability at local scales of up to a 2km resolution. RCMs can be considered useful tools for assessing climate extremes and their potential local impacts as they are able to simulate localized extreme events which GCMs simulations are unable to capture.

Outputs

This range of tools have been used to provide evidence of changes in trends and spatial distribution of extreme events in the past and for future projections across Europe, providing fundamental research to support the development and adoption of appropriate adaptation strategies.

These tools have identified the following trends in Europe regarding temperature extremes:

- Increasing frequency of warm days and nights, with the greatest increase in Southern and Central Europe and a decreasing trend northward.
- Decreasing frequency of cold days and nights across Europe.
- Heatwaves in Europe are likely to become more frequent, intense and longer-lasting, in conjunction with increasing seasonal mean temperatures. As a result, the probability of occurrence of recent events, such as the 2010 Russian heatwave, would increase substantially by a factor of 5–10 by the

mid-century. Extremely hot summer temperatures, as observed in 2003, are projected to be exceeded every second to third summer by the end of the 21st century.
- Temperatures during the hottest days are expected to increase substantially greater than the corresponding mean local temperatures in Central and Southern Europe: temperature extremes may rise by greater than 6°C.
- Winter cold extremes are expected to become rarer on average.

Regarding precipitation extremes:
- Across Europe, there will likely be a greater frequency of high precipitation and fewer moderate or low precipitation events in the future.
- Most regions will likely experience wetter winters outside of the Mediterranean and drier summers.
- Europe will likely experience greater climate polarisation, with drier conditions expected in Southern Europe and wetter conditions in Northern Europe.

ADAM,[32] the EU Adaptation and Mitigation Strategies project, provides a list of adaptation options for extreme events such as drought, flooding, heatwaves and sea-level rise. This project also provides an inventory of good practice measures in relation to a range of hazards and contexts. Meanwhile the ESPON[33] programme provides pan-European evidence and knowledge regarding territorial structures, trends, perspectives and policy impacts, and facilitating comparisons between cities and regions.

Strengths and weaknesses

Strengths	Weaknesses
These tools identify changes in climate extreme event patterns' distribution at a local scale.	Uncertainties associated with climate models are predominately due to different emission scenarios, model parameterization and dataset reliability.
They provide a method for rapid assessment of climate change impacts, predominately with regards to temperature and precipitation, but also including wind, sea level rise and other climate hazards.	

[32] www.adam-disaa.eu/
[33] https://www.espon.eu/

Suitability for rapid assessment

The tools for the investigation of spatio-temporal pattern changes can be used to support rapid analysis and assessment of risk since they can simplify comparisons and evaluation phases. On the other hand, it is not simple to produce the indicators, mainly due to the significant quantities of input data. Thus, rapid analysis strongly depends on a case by case basis.

Research gaps

Due to the requirement to download significant volumes of data, it is still challenging for end users to produce these indicators. The implementation of online climate analysis systems directly on the hosting data servers is the object of ongoing work, and has been only partially achieved by current online tools such as NCAR CMIP analysis platform,[34] NOAA Climate change portal,[35] KNMI Climate Explorer,[36] the Data Integration and Analysis System program[37] and Climate Data Store Toolbox,[38] among others.

[34] https://www2.cisl.ucar.edu/resources/cmip-analysis-platform
[35] https://www.esrl.noaa.gov/psd/ipcc/cmip5/
[36] https://climexp.knmi.nl/start.cgi
[37] https://www.diasjp.net/en/service/cmip5/
[38] https://cds.climate.copernicus.eu/toolbox/doc/tools/cdstoolbox.climate.compute_extreme_index.html

1.2.4 Multi-risk, compound and composite analysis

Multi-, compound and composite risk models assess the exposure, vulnerability and risk stemming from multiple hazards that include independent, cascading, concurrent and triggering disasters. These multi-risk assessments can be used to analyse the benefits of climate adaptation measures.

Users and application

The end users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	
Business and industry (private sector).		x	
Research	x	x	x
Civil society and NGOs.		x	x

Multi-risk models are primarily used in:

- Step 1: Assessing risks and vulnerability to climate extremes and climate change
- Step 2: Identifying adaptation options
- Step 3: Assessing adaptation options.

The models are used to assess the combined risk of multiple hazards or, in decision-support tools, to inform decision makers on prioritizing and optimising adaptation measures (Scolobig *et al.*, 2017). The model outputs highlight the expected impacts and risk of multi-hazards or compound events.

Model and tool methodology

There are two main types of multi-hazard, compound and composite risk models: those that sum the risk of individual hazards and those that account for the cumulative effects (Terzi *et al.*, 2019; Kappes *et al.*, 2012; Gill and Malamud, 2016).

A novel way of assessing multi-hazard, compound and composite risk models is through storytelling, a method which supports the simulation of events and their impacts (Zscheisschler *et al.*, 2017). Storylines can be developed in two different ways: using historic events and manipulating these with future climate or adaptation conditions; or selecting a story from a large, synthetically generated event set.

An alternative method of analysing compound and multiple extreme climate events is through multivariate analysis (Zscheisschler and Seneviratne, 2017; Leonard *et al.*, 2014). This supports users to account for multiple variables that are responsible for causing extreme impacts that cannot be captured using univariate analyses.

Forensic investigations of disasters (FORINs) are used for analysing how cascading hazards develop into cascading disasters as they support the identification of the root causes and the dynamic processes of risk drivers through an integrated, interdisciplinary and comprehensive analysis of the causes and consequences of disasters (Cutter, 2018).

Other relevant methods for describing complex relations within multi-risk components and evaluating uncertainty across risk scenarios are the Bayesian Network (BNs) approaches. BNs, also known as Bayesian Belief Networks, are probabilistic graphical models representing a set of random variables and their conditional interdependencies via a Directed Acyclic Graph (DAG) (Pearl, 1988), thus using probability distributions (marginal and conditional) to describe the relationships between system components (Borsuk *et al.*, 2004). As the outputs are graphical, BNs represent a valuable tool for the management of complex environmental issues, facilitating the involvement of experts and stakeholders in the evaluation process (Aguilera *et al.*, 2011) and a transparent and effective communication of results to potential end-users (Sperotto *et al.*, 2017).

A wide group of approaches which represent non-linear behaviour within complex systems on a macro-level are System Dynamic Models (SDMs). SDMs are based on the analysis of the aggregated dynamics of systems components whose systemic behaviour cannot be explained in terms of the simple sum of single components. SDMs have been widely used to describe dependencies and interactions among different elements of a complex system, with the main aim of identifying leverage points: sub-sections of systems' trigger changes on the wider system. By identifying these leverage points, research could be conducted on possible measures to influence these points.

Another important multi-risk modelling approach for climate multi-risk assessments are Event and Fault Trees (EFTs). Similar to BNs, these logic diagrams are composed of nodes connected by means of branches identifying different event scenarios. Each event is characterised by a defined probability of occurrence, making these tools useful in identifying and modelling chains of events that lead to risk processes (Dalezios, 2017). These methodologies have found wide applications in the field of safety engineering to identify the causes of infrastructure failures and the best methods to reduce them (Ruijters and Stoelinga, 2015; Rosqvist *et al.*, 2013; Clifton and Ericson, 2005). Fault trees have been used to trace the events that can contribute to an accident or failure, while event trees consider the consequences due to an accident, hence the identification of mitigation strategies (Sebastiaan *et al.*, 2012).

Finally, Agent-Based Models (ABMs), are used in the field of multi-risk assessment for their capacity to evaluate social interactions and dynamics towards, in this setting, multiple hazards at the macro level (see section 4.1 for more information regarding ABMs) (Gilbert and Troitzsch, 2005; Janssen, 2005). Within this field, ABMs are used to describe the ensemble of system dynamics of agents, the environment and time. These elements interact according to natural and social sciences rules, derived from physical-based and behavioural theories, creating an overall dynamic developing beyond the simple aggregation of individual entities.
Recent advancements in multi-risk assessments, due to new technological innovations such as earth observations, drones and social media (Lokers *et al.*, 2016), have developed spatio-temporal datasets for environmental applications through increasing

the volume of generated and stored data; the variety of type and nature of data; and velocity at which data is generated and processed to meet the demands and challenges of growth and development. The availability of big data has provided researchers new methodological approaches and tools, increasing the potential of big data analytics (Castruccio and Genton, 2018) including the application of Machine Learning (ML) techniques to solve a range of complex environmental issues. Specifically, ML algorithms (Corinna and Vladimir, 1995; Li and Yeh, 2002) have become increasingly applied in the field of climate change risk appraisal due to their high performance in processing big datasets and modelling complex phenomena with sufficient iteration and detail (Caldecott *et al.*, 2018).

The most widely applied methodologies are Artificial Neural Network (ANN), Random Forest (RF) and Super Vector Machine (SVM). ANN are a family of machine learning models, inspired by biological neural networks, and are typically used to estimate or approximate non-linear functions that are dependent on multiple independent variables (Li and Yeh, 2002). The RF method is a robust, nonparametric approach for modelling and classification of large nonlinear, noisy, and multivariate correlated data (Belgiu and Drăgu, 2016). Finally, SVM is based on a statistical approach performing classification of data by finding the hyperplane which maximize the margin among different classes. The vectors (cases) that define the hyperplane are the support vectors (Sayad, 2017).

Assumptions

There is a general recognition that the modelling of multi- and composite hazard risks require improvement in understanding of multi-risk dynamics through incorporating changes in exposure, vulnerability and hazard interactions (Formetta & Feyen, 2019). Models that incorporate a single hazard to assess multi-risk assume that risk is linear and that there are no interactions between the different hazard drivers, hazards or risks. However, the impacts of compound or composite disasters can be greater than the sum of their components, leading to a potential underestimation of the overall risk (Kappes *et al.*, 2012; Marzocchi *et al.*, 2012).

Another common assumption made is that adaptation measures, which are implemented to decrease the risk of one hazard, does not affect the risk level of a different hazard. However, adaptation measures can unintentionally increase the risk towards some other hazards.

The use of qualitative data, such as the use of expert or stakeholder elicitation when data learning cannot be applied because data or measures are missing or totally lacking, can be represented in the model as a problem for accurate simulations. Whenever qualitative data is employed, it can become challenging to establish a methodology to accurately calibrate the model, which could affect the accuracy of the simulation's results. This use of qualitative data could be applied, for example, for agricultural knowledge.

Model verification

Multi-, compound and composite risk adaptation model outputs can be validated using two methods:

- Data-based validation, which measures the predictive accuracy using error rates comparing the frequency of the predicted results with observe data (Kragt, 2009). Global databases on disaster losses, such as EMDAT, NATCAT and DesInventar, can be used to validate these outputs (Zehra Zaidi, 2018).
- Qualitative evaluation using expert judgement or comparing results with peer reviewed literature or similar model results (Kragt, 2009).

However, performing robust quantitative/data-based validation can be challenging. The optimal validation method would be a comparison with an independent observational dataset. However, this is not always feasible given detailed and large quantities of training data are required to calibrate and validate the models, including directly observed data, probabilistic or empirical equations, outputs from model simulations or elicitation from expert knowledge. This is especially problematic when assessing complex systems characterized by multiple stressors and variables, where large datasets are commonly lacking or difficult to retrieve. The validation of future risk projections can present a greater challenge where observations and experiences are not available, and the realised outcome cannot be correlated with any historical event.

Input data

To conduct multi-hazard, compound and composite risk models, data on the hazard drivers, exposure and vulnerability are required. The hazard and hazard driver's data require both individual hazard event sets and data regarding the interactions between different types of hazards. Generally, hazard footprints are more readily available than event sets. Exposure (raster or object-level data) and vulnerability data are required to assess the multi-, compound and composite hazard risk. Yet, multi-risk models can be integrative and support the inclusion of different and heterogeneous information sources, such as expert judgment, data and model outputs.

Outputs

Studies may provide risk, damage and loss information for a combination of hazard types or of different drivers that contribute to one disaster, and the benefits of adaptation through avoided losses.

Furlan *et al.* (2020) and Sperotto *et al.* (2019) employed Bayesian Network approaches for the multi-scenario analysis of risks arising from future climate and management scenarios. Specifically, Furlan *et al.* (2020) evaluated the probability and related uncertainty of cumulative impacts under four '*what-if*' scenarios representing different marine management options for, for example, the enhancement of the network of marine protected areas, climate conditions and rising sea surface temperature predicted for the Adriatic Sea. Similarly, Sperotto *et al.* (2019), applied a BN approach for the assessment of climate change and anthropogenic impacts on nutrients loading in freshwater environments. Here, a BN was applied to support the structuring and combining of the available information from existing hydrological models, climate change projections, historical observations and expert opinion. Subsequently, alternative risk scenarios were produced to communicate the probability and uncertainty of changes in nutrient concentrations related to precipitation and runoff across the river basin under different climate change projections of RCP 4.5 and 8.5.

In the frame of machine learning based applications, ANN algorithms have been applied in a coastal dune area of Nebraska Sandhills, USA. The aim of this work was to understand the sensitivity of dryland landscapes to future human and climate disturbances. Particularly, this ML algorithm was useful to determine the relationship between historic periods of sand deposition in semi-arid grasslands and external climatic conditions, land use pressures and wildfire occurrence (Buckland *et al.*, 2019). Eisavi & Homayouni (2016) applied an RF model to detect the shoreline evolution against tsunami events through remotely sensed data.

Strengths and weaknesses

Strengths	Weaknesses
Many countries are exposed to multiple hazards, requiring an increased understanding of their risks and the effectiveness of adaptation policies (Scolobig *et al.*, 2017).	Uncertainties in the selection of climate extremes' drivers and the hazards to consider (Forzieri *et al.*, 2016). While hazard specific uncertainties may be known, the uncertainties regarding the different interactions constitute a knowledge gap (Gallina *et al.*, 2016).
Due to climate change, which is likely to contribute to an increasing frequency and intensity of climate extremes, it is becoming increasingly important to assess the risk of compound events and tailor adaptation measures accordingly (Zscheisschler *et al.*, 2017).	Knowledge regarding different hazards is highly fragmented (Kappes *et al.*, 2012; De Ruiter *et al.*, 2017).
Multi-risk assessments support greater detailed assessments of adaptation policies' performance since they provide the overall picture of synergies among different combined risks induced by multiple hazards and/or informing decision makers in prioritizing and optimising adaptation measures.	The numerous dynamics in multi-hazard risk analysis, such as accounting for feedback loops and temporal and spatial dynamics, substantially increase the complexities of the analysis (Terzi *et al.*, 2019).
Ability and flexibility to combine multiple types of quantitative and qualitative data from heterogeneous data sources and disciplines, which can be useful when data are scarce. Data sources can include probabilistic quantities derived from expert knowledge, empirical data from preliminary studies, qualitative experiential understanding and mathematical representations.	The inclusion of different hazards, changing future exposure and vulnerability to assess future multi-risk, and design adaptation measures requires significant quantities of input and validation data.

Possibility to update models with new and greater detailed data as they become available, increasing model utility and reliability for local-scale assessment.	Large quantities of data are required for models' development.
Provides a common platform where different environmental, economic and social domains can interact together effectively.	Knowledge bias in expert elicitation.
Capability to perform scenario analysis, building on models' variables estimated using collected data.	Growing complexity of the computational effort in the case of complex systems.
The probabilistic group of models are designed to manage uncertainty, a factor that can be particularly attractive for application in the field of adaptive management, ensuring that decisions taken are based on robust quantitative estimates.	Quantitative validation is challenging and not always feasible, especially when assessing complex systems. The validation of future risk projections can present a greater challenge where observations and experiences are not available and the realised outcome cannot be correlated with any historical event.
Graphical output of these models provides a simplified visualization of complex relationships in dynamic systems, facilitating a transparent and effective communication of results to stakeholders and potential end-users.	

Suitability for rapid assessment

For high-level risk assessments, most data are readily available, for example, through OpenStreetMap[39] and HARCI-EU.[40] Extensive work is required to collate the input data and calibrate a BN model, with detailed local risk assessments requiring close collaboration with local infrastructure providers which could lengthen the assessment process. However, once this initial work has been completed, these tools can be used for rapid analysis. Several tools are available for free, such as Netica[41] and the BNLearn library[42] in R, to support Bayesian Network design and application.

Research gaps

There is currently a lack of understanding and information regarding the interactions between different hazards, as traditionally multi-hazard risk assessments simply combine different single risks. Additionally, further research is also required to explore the impacts of adaptation measures, often tailored to one particular hazard type, on the resulting risk levels for other hazards.

[39] https://www.openstreetmap.org/#map=6/42.088/12.564
[40] https://ec.europa.eu/jrc/en/publication/harci-eu-harmonized-gridded-dataset-critical-infrastructures-europe-large-scale-risk-assessments
[41] https://www.norsys.com/download.html
[42] https://www.bnlearn.com/

1.3 Exposure modelling

1.3.1 Scenarios

Scenarios are plausible descriptions of how the future may develop based on a coherent and internally consistent set of assumptions regarding key driving forces and relationships. Note that scenarios are neither predictions nor forecasts but are useful to provide a view of the implications of developments and actions. Scenarios may refer to socio-economic factors or physical transformations and can be specified at different temporal and spatial scales.

Users and application

The user groups are:

	European	National	Local/Project
Policy and public decision makers	X	X	X
Investment, finance and insurance.	X	X	X
Business and industry (private sector).	X	X	X
Research	X	X	X
Civil society and NGOs.	X	X	X

Scenarios intervene in phases:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change

Given the challenges of predicting socio-economic, climatic and environmental changes over significant timescales, scenarios are fundamental for the assessment of climate change impacts and mitigation and adaptation policies. Climate change risk can be assessed through the combined degree of hazard, exposure and vulnerability, as defined by the IPCC AR5. Climate scenarios can therefore contribute to the analysis and understanding of hazard levels, while socio-economic scenarios can contribute to substantiate the exposure and vulnerability components.

Scenarios do not provide predictions or forecasts. They can, however, establish a set of assumed “if - then” rules for future developments. Consequently, using these algorithms to emulate certain socio-economic scenarios such as population growth rates, rates of technological progress and/ or GDP growth, the causal effect on other socio-economic parameters can be examined: the evolution of energy production mixes, CO_2 emissions, but also of the population and assets to climate change risk or the cost of decarbonisation. Furthermore, climate change scenarios can set, for instance, various paths for future increases in CO_2 concentration levels that can subsequently underpin the derivation of a wide range of climate variables, including temperature, precipitation, sea-level rise, and extreme climate indices such as for heatwaves and droughts.

Model and tool methodology

There are a range of methodologies which can be used to develop scenarios. Frequently, these start from qualitative "storylines" that are subsequently translated into quantitative parameters. The quantitative components of these scenarios are dependent on which socio-economic factors the scenario explores. Scenario frameworks have been frequently used in climate change impact and policy assessments by the IPCC, although the conceptual framework driving their development principals have evolved and diversified over time. The first IPCC formal scenario exercise was the Special Report on Emission Scenarios (SRES) (Nakicenovic *et al.* 2000) exploring four main families of joint socio-economic and climatic developments. This has developed into their current forms as Representative Concentration Pathways (RCPs), Shared Socio-economic Pathways (SSPs) and Shared Policy Assumptions (SPAs) scenario matrices.

The SSPs (O'Neill *et al.*, 2014 and Riahi *et al.*, 2017) provide a common set of socio-economic data for five alternative future pathways. They include varying estimations of future population and human resources, economic and human development, technology, lifestyles, environmental and natural resources and policies and institutions (table 5).

Table 5: Starting points of SSPs. Source: Hof *et al.* (2018)

SSP	Challenges	Key elements
SSP1	Adaptation: low Mitigation: low	Sustainability: Sustainable development, low inequalities, rapid technological change directed toward environmentally friendly processes, high productivity of land.
SSP2	Adaptation: moderate Mitigation: moderate	Middle of the Road: An intermediate case between SSP1 and SSP3.
SSP3	Adaptation: high Mitigation: high	Regional Rivalry: Moderate economic growth, rapidly growing population, slow technological change in the energy sector. High inequality, reduced trade flows, and unfavourable institutional development leaving large numbers of people vulnerable to climate change.
SSP4	Adaptation: high Mitigation: low	Inequality: A mixed world with relatively rapid technological development in low carbon energy sources in key emitting regions. In other regions, development proceeds slowly, and therefore inequality remains high.
SSP5	Adaptation: low Mitigation: high	Fossil-fuel Development: Rapid economic development and high energy demand, most of which is met with carbon-based fuels. Low investments in alternative energy technologies. More equitable distribution of resources, stronger institutions, and slower population growth.

RCPs consist of emission, concentration and land-use trajectories with corresponding climate model projections. Developed for the IPCC 5th Assessment Report, they include a set of four climate forcing pathways which cover futures consistent with the 2°C goal through to high-end (>4°C) scenarios. Unlike the earlier SRES scenarios, the RCPs are not aligned to specific socioeconomic scenarios and can be combined with SSPs. This provides flexibility to explore alternative combinations of climatic and socio-economic futures.

These four RCPs span a range of future emission trajectories over the next century, each corresponding to a level of total radiative forcing (W/m^2) in the year 2100 (Table 6). The first, RCP 2.6, is a deep mitigation scenario that leads to a very low forcing level of 2.6 W/m^2, only marginally higher compared to today (2.29 W/m^2) (IPCC, 2013). This is a "peak-and-decline" scenario and is representative of scenarios that lead to very low greenhouse gas concentration levels. This scenario has a greater than 66% chance of achieving the 2°C goal. Additionally, there are two stabilization scenarios: RCP 4.5 and RCP 6.0. RCP 4.5 is a medium-low emission scenario in which forcing is stabilised by 2100. Even within this scenario, annual CO_2 emissions must sharply reduce in the second half of the century, which will require significant climate mitigation policies. Finally, there is one rising, non-stabilisation scenario, RCP 8.5, constituting a no-climate policy scenario in which GHGs continue increasing over the century and result in very high concentrations by 2100. The RCP characteristics are shown in table 6.

Table 6: RCP characteristics. Source: Hof *et al.* (2018)

Scenario Component	RCP 2.6	RCP 4.5	RCP 6.0	RCP 8.5
Average temperature change in 2100	Well below 2 °C	2.5 °C	More than 3 °C	4.5 °C
Greenhouse gas emissions relative to pre-industrial	Very low	Very low baseline; medium-low mitigation	Medium baseline; high mitigation	High baseline

Finally, in order to analyse the effect of different mitigation strategies given a specified forcing target, different SPAs have been identified (Kriegler *et al.*, 2014). All SPAs account for time periods with moderate and regionally fragmented climate action until 2020 but differ in the development of mitigation policies regarding energy (fossil fuels and industry) and land use thereafter (Riahi *et al.*, 2017).

Three different SPAs are defined both for energy and land use. For energy, one SPA assumes full regional cooperation from 2020 onwards, a second assumes a linear convergence to a global carbon tax by 2040 and the third assumes a linear convergence to a global carbon tax by 2040 for rich countries only with developing countries starting and ending convergence 10 years later.

For land use, the SPAs differ with respect to pricing of land use emissions: one SPA assumes immediate pricing at the same level as energy GHG emissions, a second SPA has limited pricing of land use emissions at 0-20% of the price on energy sector emissions and a third depicting an intermediate case between these two extremes.

In general, SPAs reflect the increasing efficiency of mitigation that is implicit in moving from SSP1 to SSP5, however, currently they do not account explicitly for adaptation scenarios. This is an important issue that should be addressed in future developments.

BOX. The Coupled Model Intercomparison Projects n° 6. Climate and social economic scenarios

Climate models are constantly being updated, in terms of spatial resolution, new physical processes and biogeochemical cycles (IPCC AR5 2013). The climate modelling community coordinates its updates within the framework of the Coupled Model Intercomparison Projects (CMIP). The goal of CMIP is to generate a set of standard simulations that each model will run. This allows results to be directly comparable across different models, to see where models agree and disagree on future changes. The upcoming 2021 IPCC sixth assessment report (AR6) will feature new state-of-the-art results from the 6th round of coupled model intercomparison CMIP6.

Specifically, the four RCPs of the IPCC AR5, have new versions in CMIP6. These updated scenarios are called SSP1-2.6, SSP2-4.5, SSP4-6.0, and SSP5-8.5, each of which result in similar 2100 radiative forcing levels as their predecessor in AR5.

One major improvement to CMIP6 scenarios is also a better exploration of possible baseline “no climate policy” outcomes. The prior generation of climate models featured in CMIP5 only included the high radiative forcing scenario RCP8.5 and the relatively little-mitigation scenario RCP6.0. CMIP6 has added a new scenario – SSP3-7.0 – which lies right in the middle of the range of baseline outcomes produced by energy system models. SSP4-3.4 is another new scenario that tries to explore the space between scenarios that generally limit warming to below 2ºC (RCP2.6 / SSP1-2.6) and around 3ºC (RCP4.5 / SSP2-4.5) by 2100. This will help scientists to greater assess the impacts of warming if societies rapidly reduce emissions, but fail to mitigate fast enough to limit warming to below 2°C. SSP5-3.4OS is an overshoot scenario (OS) where emissions follow a worst-case SSP5-8.5 pathway until 2040, after which they decline extremely rapidly with a significant use of negative emissions late in the century. Finally, SSP1-1.9 is a scenario intended to limit warming to below 1.5ºC by 2100 above pre-industrial level. It was added in the aftermath of the Paris Agreement when countries agreed to pursue efforts to limit the temperature increase to 1.5ºC.

Model verification

Given their nature, scenarios cannot be tested. However, they could be verified ex-post, which scenario amongst the many considered, is approached greatest by the phenomenon under investigation.

Input data

The bases of climate scenarios are pre-set GHG emissions and/or radiative forcing and CO_2 concentration profiles. These subsequently generate climate data for further analyses.

Outputs

Many quantitative aspects of SSPs are available at an aggregated global and regional level, such as energy supply and demand (Bauer *et al.*, 2016), land use and land cover change (Popp *et al.*, 2017), greenhouse gas emissions (Riahi *et al.*, 2017), air pollution and aerosol emissions (Mallampalli *et al.*, 2016) and mitigation costs (Riahi *et al.*, 2017). For an overview of the data of SSPs see Riahi *et al.* (2017) and the RCP database.[43]

SRES scenarios, RCPS and SSPs have been extensively applied worldwide by the scientific community and especially in the vast majority of FP6, FP7, and H2020 EC project related to climate change science.

Strengths and weaknesses

Strengths	Weaknesses
They provide a flexible and internally coherent description of the future under large degrees of uncertainty when standard forecasting methods are not applicable.	They are predominately hypothetical and speculative although internally coherent and heavily dependent upon the knowledge and subjectivity of scenario developers

Suitability for rapid assessment

Data and descriptions of RCPs and SSPs are easily accessible. Developing and applying a methodology for new scenarios is complex, especially if quantification is required using models, and therefore requires time to develop.

Research gaps

One of the limitations of SSPs was their initial specification at the "country level". An increasing number of initiatives are providing "downscaled" or gridded specification of SSPs (Murakami and Yamagata, 2016).

The implementation quantification of adaptation role in different scenario-building exercises is still less developed and consolidated than that of mitigation. This is an area of research that requires greater effort and that can support socio-economic modelling.

[43] https://tntcat.iiasa.ac.at/SspDb/

1.4 Vulnerability modelling

1.4.1 Socio-economic vulnerability

Socioeconomic vulnerability modelling can be used to compare and rank geographical units with regards to susceptibility to harm and coping capacity, predominately measured by means of indicator-based assessments (IBAs).

Users and application

Users of these models include:

	European	**National**	**Local/Project**
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

Socioeconomic vulnerability models can be applied to assess the following stages of adaptation policy cycle:

- Step 2: Assessing risks and vulnerability to climate change
- Step 6: Monitoring and evaluation

Socioeconomic vulnerability models can be used as decision support tools to capture a snapshot of the most important facets involved in assessing risk and vulnerability which can be used for monitoring, reporting and evaluation (MRE). Vulnerability indicator-based assessments are widely used to evaluate the relative values of geographic units by aggregating separate indicators into one composite index. The expected outputs can be the ranking of the geographical units based on vulnerability scores and/or scoreboards for each component of vulnerability to inform the strength and weaknesses.

Model and tool methodology

Vulnerability-driven approaches examine the socio-economic, demographic, cultural, environmental, political and institutional constituents of vulnerability and risk, which help to explain how society and individuals perceive and respond to climate-related hazards. These approaches are greatest suited as a measurement of peoples' adaptation needs, as well as their ability to cope with climate shocks (Cutter, Boruff and Shirley, 2003; Adger *et al.*, 2004; Engle, 2011; Marzi, Mysiak and Santato, 2018). The IPCC embraced vulnerability as a key constituent of risk, along with hazard and exposure. Vulnerability comprises of both "sensitivity or susceptibility to harm" and a "lack of capacity to cope and adapt" (Mach, Planton and von Stechow, 2014). Sensitivity is defined as 'the degree to which a system is affected, either adversely or beneficially, by climate variability or change'. Sensitivity is a function of hazard intensity and the properties of the exposed elements, or approximated using a set of indicators (Mysiak *et al.*, 2018). Adaptive capacity is defined as "the ability of systems, institutions, humans and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences” and refers to capabilities, resources and institutions for implementing effective adaptation measures (Marzi, Mysiak and Santato, 2018; Mysiak *et al.*, 2018).

The presence of available information on the socioeconomic dimension of vulnerability can significantly help to determine where the most vulnerable population is located (Cutter *et al.*, 2003; de Loyola Hummell *et al.*, 2016). Some studies focus on socioeconomic and demographic determinants of vulnerability denoted as “social vulnerability” which influence society’s preparedness, response and recovery (Birkmann *et al.*, 2013; Cutter *et al.*, 2013; Terti *et al.*, 2015). The social vulnerability is a measure of the tendency to suffer harm and explains the unequal impact on exposed population. Such impacts have been previously linked to a number of characteristics such as wealth, age, gender, ethnicity and accessibility to healthcare, social protection schemes and critical infrastructures (Roder *et al.*, 2017; Cutter *et al.*, 2003; Fekete, 2009; Fernandez *et al.*, 2016; Koks *et al.*, 2015; Willis *et al.*, 2014; Zhou *et al.*, 2014). The Sendai framework encourages the policy makers to formulate and implement national and local strategies and plans on climate change adaptation (CCA) on the basis of empowering and including all stakeholders, in establishing the basis for gender equality, and for including people and groups more exposed and more vulnerable to climate change impacts (UNDRR, 2019).

Indicator-based assessments are widely used to assess the relative vulnerability values of geographic units or population groups by aggregating separate indicators into composite indices and scoreboards (Fernandez, Bucaram and Renteria, 2017). Such assessments can be used to represent a characteristic of a system of interest, distil the complexity of an entire system to a single metric, inform decision-making, improve stakeholder participation, build consensus, explore underlying processes and advocacy (OECD, 2008; Tate, 2012).

Index development involves a multi-stage sequential process, which includes structural design, indicator selection, choice of analysis scale, data transformation, scaling, weighting and aggregation. ND-GAIN from Notre Dame Global Adaptation Initiative (University of Notre Dame, 2018); MOVE from EC-CORDIS (Birkmann *i*, 2013); and ESPON Climate project from the European Commission (ESPON, 2011) are the most familiar vulnerability indices used by various scholars and international agencies. In addition, the vulnerability indicators have been utilized to develop risk and resilience indices such as INFORM Global Risk Index (*INFORM - Global, open-source risk assessment for humanitarian crises and disasters*, 2018) from the Joint Research Centre (JRC); Global Climate Risk Index from Germanwatch (Eckstein, Hutfils and Winges, 2019); World Risk Index from Bündnis Entwicklung Hilf (Heintze *et al.*, 2018) and Inclusive Disaster Resilience Index (INDRIX) from the European Commission (EC, 2018).

Assumptions

The key assumptions on indicator-based models are i) structural design ii) choice of analysis scale; iii) indicators used to proxy the vulnerability components; and iv) the methodological choices to combine the indicators into a single index.

The structural design includes deductive, hierarchical, and inductive arrangements (Tate, 2012). Deductive methods with fewer indicators can be applied once the knowledge regarding the determinants of vulnerability are standardised. Until such time, inductive and hierarchal methods using numerous indicators are more appropriate.

The choice of analysis scale plays an important role on the outcomes and policy implications. A "nested" approach, for example, can be adapted to multiple scales yet some scale-specific information may not be incorporated in the analysis. Hence, multiple scale-specific assessments may not provide greater information or be as useful for policy makers (Marzi, Mysiak and Santato, 2018). Indicator choices are determined by factors such as data availability, desired number of indicators, statistical properties and how representative the indicator is of the underlying vulnerability dimension (Tate, 2012). A wide spectrum of methodological choices can be employed to normalize, weight and aggregate the indicators, which involves a certain degree of subjectivity, including linear and non-liner normalization approaches, expert-based and data driven weighting methods, and the application of compensative and non-compensative aggregation procedures (Marzi *et al.*, 2019).

Model verification

Vulnerability indices can either be internally or externally validated. External validation can be achieved using independent proxy data such as mortality, economic loss and household surveys, or actual climate change adaptation practices, documented using the appropriate monitoring, reporting and evaluation (MRE) schemes (EEA, 2015). MRE systems are currently being developed for the purpose of continuous monitoring, reporting and evaluation of the progress made in implementing climate change adaptation plans. Internal validation can be performed using global sensitivity analyses to provide a systematic evaluation of the most popular social vulnerability index configurations (Tate, 2012, 2013; Fernandez, Bucaram and Renteria, 2017; Marzi *et al.*, 2019).

Input data

No climate data is required for social vulnerability assessments. If exposure data is incorporated into the assessments, hazard levels for river and coastal floods and drought proxies, such as WASP, SPI or SPEI indices from JRC (Alfieri *et al.*, 2016; Carrão, Naumann and Barbosa, 2018; Vousdoukas *et al.*, 2018; Spinoni *et al.*, 2019) can be overlaid with population, land use and other potentially exposed elements. The exposure data for Europe can be attained from JRC PESETA projects (JRC, 2018).

Indicator choices are determined by factors such as data availability, desired number of indicators, statistical properties and how representative the indicator is of the underlying vulnerability dimension, sector and application. Table 7 summarises indicators previously used for sensitivity and adaptive capacity research (Marzi, Mysiak and Santato, 2018; Mysiak *et al.*, 2018).

Table 7: sample set of sensitivity/susceptibility and adaptive capacity indicator can be used in socioeconomic vulnerability assessment.

Sensitivity/Susceptibility		Adaptive Capacity	
Dimension	**Indicator**	**Dimension**	**Indicator**
Manufactured Capital	Urban areas	Economic resources	Gross Domestic Product (GDP)
	Industrial areas		Distribution of the household income (GINI)
	Impervious surfaces		At-risk-of-poverty rate
Natural Capital	Forest areas	Infrastructures	Extension of the infrastructure (road and railways)
	Natural Protected Areas		Irrigated and Irrigable land
	Soil erodibility		Share of the protected lands
Social Capital	Population density	Knowledge and Technology	Total expenditure for R&D
	Structural dependency index		Patent applications to European patent office (EPO)
	Age dependency		Electricity consumption of agricultural enterprises
Economic Capital	Gross added value - agriculture	Institutions	Institutional Quality Index
	Gross added value - industry		Corruption Perceptions Index
	Gross added value - services		Perceived independence of the justice system

Several other indicators have been used in other similar studies, such as the World Risk Index (Heintze *et al.*, 2018), INFORM GRI (Marin-Ferrer, Vernaccini and Poljansek, 2017) and Europe Climate Risk typology (RESIN, 2018). The World Risk Index accounts for social vulnerability indicators such as gender, equality, housing conditions, medical services and public health expenditure. On the other hand, INFORM GRI accounts for uprooted people (refugees and displaced population), health condition and food security. The data can be extracted from multiple sources such as Eurostat, Copernicus and EEA databases.

Outputs

Outputs include i) vulnerability maps illustrating relative vulnerability scores for targeted geographical units and/or population groups, ii) internal validation of the method by means of uncertainty/sensitivity analysis performed using various model configurations.

There have been several attempts to develop indicator-based vulnerability assessments at both a global and European level. Indices include: ND-GAIN from Notre Dame Global Adaptation Initiative (University of Notre Dame, 2018); MOVE from EC-CORDIS (Birkmann *et al.*, 2013); ESPON Climate project from the European Commission (ESPON, 2011); INFORM Global Risk Index (*INFORM - Global, open-source risk assessment for humanitarian crises and disasters*, 2018) from JRC; Global Climate Risk Index from Germanwatch (Eckstein, Hutfils and Winges, 2019); World Risk Index from Bündnis Entwicklung Hilf (Heintze *et al.*, 2018) and Inclusive Disaster Resilience Index (INDRIX) from the European Commission (EC, 2018). These encompass vulnerability indicators either in the form of composite indices or scoreboards. Among these, INFORM has gained increasing global coverage due to its simplicity, transparency in communication and data, and annual updates since 2015. The index has been endorsed and integrated by several national and international organizations and agencies such as the European Commissions' Humanitarian and Civil Protection Office (ECHO), the Office for Coordination of Humanitarian Affairs (OCHA), the UK Department for International Development (DFID), the World Food Programme (WFP), the United Nations International Children's Emergency Fund (UNICEF), US Department of State and the US Agency for International Development (USAID) (Marin-Ferrer, Vernaccini and Poljansek, 2017).

Strengths and weaknesses

Strengths	Weaknesses
▪ Ability to minimise the number of indicators without loss of the underlying information base. ▪ Can produce a baseline for vulnerability assessments. ▪ Supports continuous monitoring, reporting and evaluation (MRE) which enables policy makers to identify the existing trends and progress. ▪ Enables communication with the general public (citizens, media) and promotes accountability. ▪ Enables users to effectively compare complex vulnerability dimensions.	▪ To construct an index, developers are required to make arbitrary choices at different stages of the construction procedure. These steps include the selection of social vulnerability indicators, data transformation, weighting and aggregation. By choosing different methods, the results may change, and this may lead to mis-informed policies. To mitigate this, an uncertainty/ sensitivity analysis should be performed. Scale-dependency of vulnerability indices and data availability issues, especially at finer resolutions. ▪ Deductive methods which may be more informative and robust, can only be applied once the knowledge regarding the determinants of vulnerability are greater established.

Suitability for rapid assessment

Rapid access to input data depends on the geographic location and scale of the analysis. For instance, most of the required indicators for social vulnerability assessment in Europe are available at NUTS 2 level Eurostat database. Nevertheless, moving to NUTS 3 level and finer resolutions reduces the speed of the process due to data availability and scale-dependency issues. To support design structure and methodology, there are several studies which can provide a reference/benchmark, including ND-GAIN (University of Notre Dame, 2018), MOVE (Birkmann *et al.*, 2013), ESPON Climate project (ESPON, 2011), Cutter, Boruff and Shirley (2003) and Fekete (2009).

The indicator-based assessments are designed to enable rapid screening for policy purposes. Such assessments constitute predominately two tiers: i) rapid screening which is cost effective, and ii) robustness and sensitivity analysis in which the cost of analysis increases. Numerous studies only apply the first tier of cost-effectiveness. However, to increase the robustness and avoid misinformed policy applications, the developers are encouraged to implement the second tier as well.

Research gaps

Data availability varies according to the scale of analysis (national, regional, provincial or municipal administrative levels). As previously discussed, most of the social vulnerability indicators in Europe are available either on NUTS2 or NUTS3 administrative levels. To perform analysis at finer resolutions, such as at municipal or local scales, developers have to either use the countries' census data as demonstrated in Marzi *et al.* (2019) or peruse stakeholder-driven approaches (Linkov and Trump, 2019).

The main gap associated with these socio-economic vulnerability models are embedded in the validation procedure, of which there are two key approaches: i) empirical (external) validation of the indices using observed disaster losses, fatalities, and disaster declarations (Bakkensen *et al.*, 2017); and ii) internal validation using global sensitivity analyses to provide a systematic evaluation of the most popular social vulnerability index configurations (Tate, 2012, 2013; Fernandez, Bucaram and Renteria, 2017; Marzi *et al.*, 2019). Empirical validation is highly dependent on data availability at certain temporal and spatial scales, especially at collective scales, which limits such analyses. On the other hand, few social vulnerability studies have applied a systematic evaluation to assess how variations in methods affect the output rankings: external validation (Tate, 2012). In addition, the methodological choices applied to construct such indices can be improved. For instance, employing non-linear normalization methods or fuzzy aggregators may lead to additional insights.

As highlighted in Marzi, Mysiak and Santato (2018), multiple scale vulnerability assessments could be more informative and useful for policy makers than scale-specific ones. There are few studies investigating socio-economic vulnerability at several collective and community levels which regard scale-dependency issues. In addition, few studies have conducted vulnerability assessment at the local level using fine resolution data, such as census or municipality units (Roder *et al.*, 2017; Marzi *et al.*,2019).

1.4.2 Ecosystem vulnerability

This chapter describes models and techniques to assess climate change impacts on ecological vulnerability. Ecological vulnerability is the degree to which a system, such as an ecosystem, is susceptible to and unable to cope with the adverse effects of climate change (IPCC, 2007).

Users and application

End-users of the model include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

Ecological vulnerability models are used in:

- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options
- Step 6: Monitoring and evaluation

Ecosystems provide multiple ecosystem services. Climate change results in large changes in ecosystem service supply through impacting, for example, food production and water supply (Schröter *et al.*, 2005). Ecosystem vulnerability assessments are thus important to safeguard ecosystem services as well as protecting and conserving natural assets (Weißhuhn, Müller and Wiggering, 2018). To support decision-making and ecosystem management, the analysis of an ecosystem's vulnerability provides information regarding ecosystem weaknesses as well as its capacity to recover after experiencing a negative impact.

Model and tool methodology

Vulnerability is a function of three aspects: susceptibility to exposure, sensitivity to the stressor and adaptive capacity or recovery potential (Lange, Sala, Vighi and Faber, 2010; Weißhuhn *et al.*, 2018). Often, different models are applied to assess each vulnerability aspect, after which the results are combined into a vulnerability indicator.

Exposure

Exposure is generally modelled for each hazard or stressor separately, such as drought, sea level rise, flooding, erosion and fires. Exposure can be assessed as the probability of a disturbance or spatial proximity to a disturbance (Frazier, Thompson, & Dezzani, 2014). Another option is to analyse the number of spatially located system elements that are affected by a given disturbance. For example, this could involve determining the area of the ecosystem under threat (Dong *et al.*, 2015). Hazard assessment models can be used to calculate the exposure indicators.

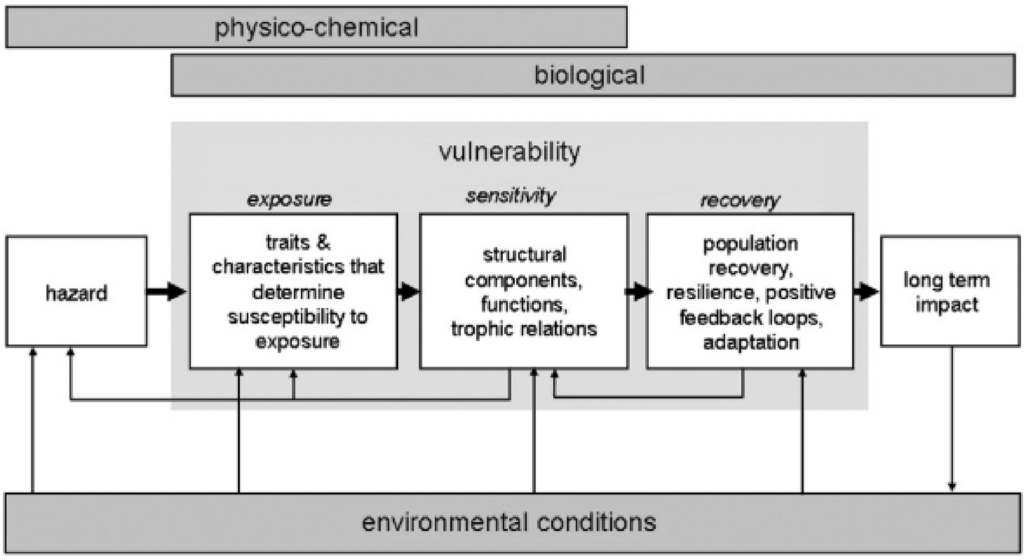

Figure 4: General framework for ecological vulnerability assessment for hazard or interaction of hazards. The top bars indicate whether physico-chemical or biological characteristics are the main determent (or both). Environmental conditions have an influence on all aspects but are also influenced by the long-term impact. Figure by Lange et al. (2010).

Sensitivity

Sensitivity can be assessed using indicators specific for the ecosystem and exposure. Examples of these indicators include: elevation of coastal wetlands exposed to sea level rise, water flow volume in river ecosystems, or the abundance of fish species sensitive to habitat loss in a coral ecosystem exposed to bleaching (Weißhuhn *et al.*, 2018). Many aspects of ecosystem sensitivity are derived from the inherent characteristics of species, such as functional traits, which can be used as input parameters for sensitivity analyses (Gritti, Smith, & Sykes, 2006). Examples of sensitivity models include GOTILWA+ (Schröter *et al.*, 2005) and Lund-Potsdam-Jena-Guess (LPJ-Guess) models (Smith *et al.*, 2001).

Adaptive capacity

Literature on assessing the adaptive capacity of ecosystems is scarce (Weißhuhn *et al.*, 2018). Overall, it appears that the adaptive capacity of ecosystems originates predominantly from the biological entities in relation to species and their genetic characteristics, rather from the abiotic ecosystem components. However, this is challenging to measure. Therefore, the analysis of ecosystem adaptive capacity could be approached through assessment of organism communities and their interrelations, as well as the relative degree of undisturbed ecosystem present (Watson, Iwamura, & Butt, 2013). Methods to assess the adaptive capacity are the adaptive capacity index (Metzger, Rounsevell & Acosta-michlik, 2006) and measuring the ecosystem intactness (Watson *et al.*, 2013).

Vulnerability indicators

Combined, the exposure, sensitivity and adaptive capacity provides a comprehensive assessment regarding the level of vulnerability of an ecosystem. These results are often aggregated into vulnerability indices (Frazier *et al.*, 2014; Preston, Yuen, & Westaway, 2011). Principal component analysis (PCA), or other factor reduction methods, are commonly used to reduce large numbers of vulnerability indicators into one or a small number of vulnerability indices (Abson, Dougill, & Stringer, 2012; Preston *et al.*, 2011). Regional vulnerability assessment (ReVA) (Boughton, Smith, & O'Neill, 1999) and the Spatially Explicit Resilience-Vulnerability (SERV) model (Frazier *et al.*, 2014) can be used to identify which ecosystems are most vulnerable on a regional scale. Further, expert judgement is often used to assess vulnerability when data is scarce (Halpern *et al.*, 2007).

Assumptions and model verification

The choice of vulnerability indicators can have a significant effect on the vulnerability score outcome and should thus be carefully chosen. Managing uncertainty in ecological vulnerability mapping can be addressed through performing sensitivity analyses and/or using multiple alternative climate change scenarios.

Input data

Ecosystem vulnerability assessments require input from multiple biological community characteristics, such as community structure and functioning, sensitivity of the community, habitat vulnerability and recovery capability (Lange *et al.*, 2010). If possible, they should use stressor/ hazard-specific environmental indicators that includes information on exposure, sensitivity and adaptive capacity of an ecosystem (Weißhuhn *et al.*, 2018). When information at a species level is unavailable or challenging to obtain, it is possible to use functional trait groups as inputs for ecosystem models (Gritti *et al.*, 2006).

Climate variables that are most commonly used in vulnerability studies are temperature, precipitation, flood and drought (Sherbinin *et al.*, 2019). These data can be used to model multiple future scenarios, with confidence intervals bounding the results. In addition, many ecological vulnerability models examine the impact of land use change as a non-climatic stressor (Metzger *et al.*, 2006; Sherbinin *et al.*, 2019).

It is important to consider the implications of spatial scale on assessing ecosystem vulnerability (Fekete, Damm & Birkmann, 2009). Many vulnerability studies have a strong local orientation (Preston *et al.*, 2011), requiring high resolution data. If local data is not available, vulnerability assessment can be performed on, for example, a regional, national or global scale (SOPAC, 2005; Watson *et al.*, 2013). Further, processes and determinants can have multi-scale effects, and spatial scale differences among data sources can be significant (Preston *et al.*, 2011).

Outputs

The results of ecosystem vulnerability assessments are often summarized as vulnerability maps. This is a spatially-explicit output that is a powerful tool to inform policy-makers, researchers and the wider community (Weißhuhn *et al.*, 2018). In such maps, however, a significant proportion of information is lost. It is, for example, not possible to compare different drivers when comparing vulnerability scores. Watson *et al.* (2013) highlight how greater detailed ecological vulnerability assessments can be used to inform adaptation planning and conservation strategies, with specific attention to vegetation intactness as a measure of adaptive capacity.

As such, there is a trade-off between information-richness and communicability (Abson *et al.*, 2012). Key considerations when balancing this trade-off is the target audience and the presentation format of an ecological vulnerability assessment: single or aggregated indices are suitable for the general public or policy applications, whereas multiple indicators or raw data can be used to inform researchers.

Relevant application (low data availability)

The Environmental Vulnerability Index (EVI) is a synthesis framework for understanding the environmental vulnerability of countries (SOPAC, 2005). It is designed for use at the national scale but could be evaluated at a range of geographic scales, including regions and provinces, and can be used when data availability is scarce. EVI scores have been calculated for a large number of countries. The results are used for identifying and prioritising issues requiring action, developing policies to reverse environmentally destructive trends, and as a guide for legislation and resource management. EVI reports for countries are organized as a single-page, information-dense report card. These cards present the results for vulnerability, hazards, resistance and damage, and the percentage of indicators relevant to each for which data were available.

Relevant application (high data availability)

The Ecosystem Vulnerability Assessment Approach (EVAA) was developed by Brandt *et al.*, (2017) to determine the potential vulnerability of forest ecosystems to climate change over the next 100 years. The approach has been successfully applied to support forest management decisions across the Midwest and Northeast of the USA by non-governmental, private, and government forest managers. EVAA combines multiple quantitative models with expert elicitation from scientists and land managers, using a seven-step approach. Experts interpret the results of climate projections, habitat suitability models and landscape process models to assess climate change impacts and their interactions and adaptive capacity factors to determine ecological vulnerability and uncertainty.

Strengths and weaknesses

Strengths	Weaknesses
Ecological vulnerability models are a valuable tool to assess the impact of climate change on the spatial distribution and health of ecosystems. Since ecosystems provide services that are crucial for human wellbeing, knowledge on ecological vulnerability is an essential addition to the more common socio-economic vulnerability climate assessments.	For local modelling to inform planning and management, detailed data and information is needed regarding ecosystem functioning which is not always available. Larger-scale and more ‘simple’ vulnerability maps can be created with limited data, but these do not provide information regarding the key stressors which impact vulnerability and are thus of limited use for decision-makers.

Suitability for rapid assessment

A rapid assessment could be conducted based on expert judgement or using tools that can manage low-data availability, such as the EVI (SOPAC, 2005). To inform decision-making, however, it is advised to conduct a comprehensive assessment with attention to the selection of vulnerability indicators, methodology and dealing with uncertainty.

Research gaps

Preston *et al.* (2011) identified the key challenges related to methods of climate change vulnerability mapping: a lack of ‘best practices’ due to only a small proportion (ca 5%) of climate vulnerability assessments focussing on ecosystems (Sherbinin *et al.*, 2019); a lack of robust data at the relevant scale and a lack of consistency among data sources; limited attempts to manage uncertainty and validation; and paucity of spatially explicit and internally consistent scenarios.

1.4.3 Resilience analysis and assessment

Resilience definitions range from narrowly defined engineering principles (Hashimoto *et al.*, 1982) to more comprehensive definitions that encompass complex socio-economic and ecological systems. For example, in the context of climate change: "The capacity of social, economic and environmental systems to cope with a hazardous event or trend or disturbance, responding or reorganising in ways that maintain their essential function, identity and structure, while also maintaining the capacity for adaptation, learning and transformation" (IPCC, 2018). Resilience is a systems property relating to its ability to respond to disturbances caused by climate-induced extremes, such as heatwaves and storms, and trends, including sea level rise. Absorption, recovery, adaptive and transformative capacity are key characteristics of a resilient system (OECD, 2014). However, adaptation often focuses on actors while resilience focuses on systems (Nelson *et al.*, 2007). The greater the complexity of a system, the greater the challenge to comprehensively assess its resilience (Boltz *et al.*, 2019). Nevertheless, resilience assessments are important to guide decision-making and to track the progress towards enhanced resilience to climate change.

Users and application

End users of these frameworks and tools include:

	European	**National**	**Local/Project**
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

Resilience frameworks and tools can be applied to assess various stages of adaptation policy and decision making:

- Stage 1: Preparing the ground for adaptation - assessing the 'climate readiness' of a system and the requirement to develop greater resilience to climate hazards.
- Stage 2: Assessing the risks and vulnerability of systems to climate change - climate hazard vulnerability is intrinsically linked to resilience. Assessing hazards, preparedness, response, impacts and recovery provides a comprehensive overview on the system's ability to function during hazards or restore functions after a disturbance.
- Stage 4: Assessing adaptation options – assessing the ability of options to strengthen system resilience.
- Stage 6: Monitoring and evaluation – monitoring progress in adaptation through ongoing assessment of adaptation measures' ability to increase system resilience.

Resilience assessments can:

- support strategic planning - spatial planning, design codes for buildings and infrastructure, integrated water resource management (IWRM), urban planning and risk management of climate hazards such as heat, floods and droughts.
- support the identification of effective policies to enhance resilience, such as protection and mitigation measures, insurance schemes including distribution of costs over time and persons, and recovery capability enhancement.
- enable progress monitoring of resilience development.
- justify targeted investments.
- prioritise policy implementation.

Resilience assessments, in conjunction with reliability and robustness assessments of adaptation options, are key to informed and holistic decision-making (CRIDA, UNESCO, 2018). The outputs from resilience assessments can promote the implementation of adaptation measures (de Bruijn *et al.*, 2018), supporting the comparison of multiple adaptation options' effectiveness for building resilience (Wardekker, 2018) and supporting the design of dynamic adaptation pathways (Haasnoot *et al.*, 2019) (section 5.6).

Model and tool methodology

There are multiple frameworks and tools, which contribute to resilience assessments. A resilience assessment starts with a scoping phase to determine:

- the system delineation that identifies the system components to include and exclude in the analysis.
- the type and number of indicators that describe key resilience abilities relevant for the system and hazard in consideration.

For example, when assessing the resilience of a city to flooding, the city constitutes the system and indicators may relate to the severity and duration of interruption caused by floods. The system's response to a disturbance or trend, therefore, also depends on the resilience of the individual system components. If economic activities and social well-being depend on critical infrastructure, the number of people affected by an interruption in services of the critical infrastructure and the duration of the interruption may be used as an indicator for resilience (De Bruijn *et al.*, 2019). Resilience assessments may also be hazard neutral, such as the City Resilience Index (CRI, 2016a) which aims to describe the general capacity of a city to survive, adapt and thrive independent of its exposure to chronic stresses or acute shocks.

Resilience can be assessed at different scales: for individuals, communities, cities or nations. To assess the resilience of large groups, general indicators of their resistance and recovery capacity could include their level of education, household income or insurance rate. These indicators are proxies for the ability to withstand and repair losses or, alternatively, they can highlight the likelihood that people need to adopt unsustainable solutions to survive, for example, by selling the means which sustain their livelihoods and productivity in the long term.

The range of available tools to assess resilience reflects its wide range of definitions. Examples of assessments for narrowly defined systems include "Criticality" for road networks (Lincke *et al.*, 2018; van Ginkel *et al.*, 2019) and "Circle" for critical infrastructure (Hounjet *et al.*, 2016). Examples for complex systems such as cities include the "City Resilience Framework" developed as part of the Rockefeller Foundation's "100 Resilient Cities" (hereafter 100RC) initiative (ARUP, 2015) and the "Resilience Maturity Model" (SMR Project, 2018).

Several types of tools and methods can be distinguished:

- Models to analyse hazards & impacts also used in risk assessments
- Frameworks to describe resilience characteristics of systems
- Methods to obtain resilience specific information from stakeholders
- Methods to visualise disruption of society and the effect of measures
- Methods to support adaptation options

Models to analyse hazards and impacts also used in risk assessments
Models to analyse hazards, such as hydrodynamic models, wind models and statistical methods of rainfall/temperature, and their direct and indirect impacts, such as flood damages and droughts, provide crucial input for resilience assessments.

Frameworks to describe resilience characteristics of systems
Frameworks such as the City Resilience Index (CRI, ARUP, 2016) provide insights regarding the resilience of a complex system with multiple components - in this context, for a city. Such frameworks are typically based on the indicators or characteristics which determine the impacts and recovery, and support qualitative, semi-quantitative or quantitative evaluation of resilience and the effect of resilience enhancing measures. For the development of the CRI, an extensive literature review and consultations with experts and city stakeholders were conducted to identify the indicators that influence city resilience (CRI, 2016a). The CRI comprises of 52 indicators in line with the four key dimensions of "Health & wellbeing of people", "Economy & society", "Infrastructure & ecosystems" and "Leadership & strategy" (CRI, 2016a). The measurement guide (CRI, 2016b) details how to assess each indicator. For each indicator, the guide describes the range of best- and worst-case scenarios to be used in qualitative assessments and makes recommendations for quantitative metrics, such as the number of homeless people to inform the indicator "safe and affordable housing".

Methods to obtain resilience information from stakeholders
Risk models alone do not provide enough information on hazard impacts since they often aggregate information or they insufficiently capture intangibles, indirect effects, recovery aspects and learning abilities. Specific information regarding those effects within complex environments can be obtained through methods such as:

- CIRCLE, a tool which supports the structuring of workshops and to obtain information on cascading effects of critical infrastructure disruption on other networks and on society (figures 5 and 6) (section 2.9).
- the storyline method, which can guide stakeholders through fictional events to gain insights regarding the required assumptions, the actions and reactions of stakeholders, the effects on society and recovery (De Bruijn *et al.*, 2016). Storylines assist stakeholders to estimate relevant consequences, cascading effects and repair times or alternative options, while, for example, abstract

questions or aggregated complex risk information may constitute a greater challenge to link to stakeholders' practices.

Figure 5: Example of a CRI resilience profile. From: https://www.cityresilienceindex.org/#/city-profiles

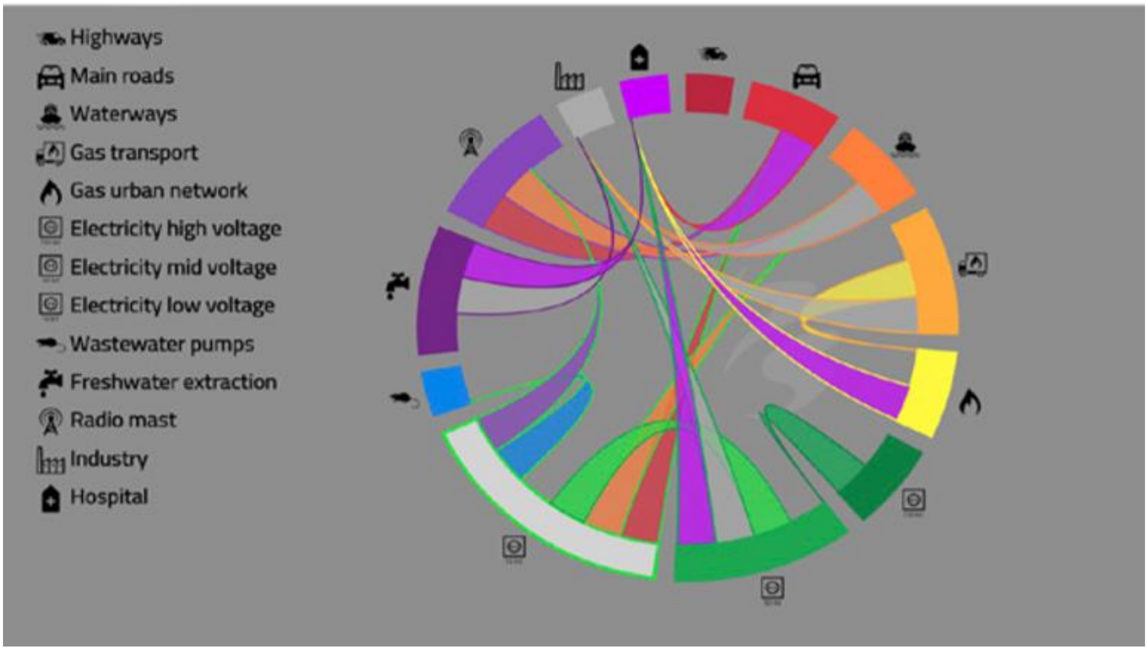

Figure 6: Example of critical infrastructure dependencies in Circle and their relevance (indicated by the width of the connecting bands). From: https://www.deltares.nl/app/uploads/2015/04/Productblad-CIrcle.pdf

Methods to visualise disruption of society

Methods that quantify disruption over time are available to attain an overview of the impacts and recovery magnitudes and timescales which may also be used to quantify the effect of resilience-enhancing measures. These effects could be visualised, for example, as system response curves and expected number of person disruption days (Murdock *et al.*, 2018).

Methods to support adaptation options

Finally, there are guiding principles, frameworks and tools to support the identification and assessment of adaptation options that increase resilience, such as the Climate Adaptation Support Tool (Climate-ADAPT, 2020).

Assumptions

System resilience can be assessed in relation to both historic and projected future events. To assess resilience to historic hazards and impacts, existing data regarding recovery times and cascading effects could be used. However, assessing potential future hazards, impacts and, in particular, recovery and cascading effects pose a greater challenge. Assumptions need to be made regarding repair rates, recovery times and which characteristics determine this recovery. Further, assumptions regarding future changes in climate, socio-economic pathways and societal preferences are required.

Model verification

Given that numerous tools and methods use semi-quantitative or qualitative methods, the traditional validation technique of comparing against quantitative observations is not possible. Therefore, in order to validate or verify these models and tools, a plausibility check by the stakeholders is required, which verifies their added value, usability and the implications of the outcomes. This could be conducted using historic events or comparisons between storyline analyses. Since resilience cannot be measured directly in the field and requires the use of indicators, the verification of tools focus on:

- are the used assumptions correct and are the components of the methods validated, such as the physical models and data used?
- do the indicators combined provide a comprehensive overview of the impact and recovery from hazards, the learning aspects and adaptability?
- do the indicators sufficiently capture the effect of changes and measures and support decision-making?

If a plausibility check is conducted, a further sensitivity analysis could test the assumptions' robustness and how differing assumptions would alter the results of the resilience assessment. The CRI, for example, was validated through consultation of 12 external and 10 internal experts (CRI, 2016a).

Input data

These frameworks require climate outputs from hazard models to determine the systems' resilience towards hazardous events. For example, climate data such as rainfall intensity for various durations, temperature and storminess are required to assess drought hazards or flood hazards as well as their associated probability density functions. Additionally, trends in rainfall, temperature and discharges may be required.

Dependant on the specific context, a large variety of socio-economic, environmental, physical and governance variables are also required to describe the context-specific indicators:

- Bio-physical data, such as protection measures, vegetation and elevation
- Critical infrastructure dependencies and sensitivity to climate hazards
- Socio-economic data including economic activities, land use and number of citizens
- Demographic data including age, level of education, income, unemployment rate and different social groups
- Networks and preparedness such as participation in Covenant of Mayors, crisis management organisations and churches or The Red Cross.

Outputs

Resilience assessments can indicate the degree of resilience within a system using categorised stages for a specific hazard at a given time. The Resilience Maturity Model defines resilience stages as starting, moderate, advanced, robust and vertebrate (SMR Project, 2018). It can also identify key characteristics which could enhance resilience.

Case study: methods and tools supporting urban resilience planning - experiences from Cork, Ireland (de Bruijn *et al.*, 2018)

Cork is located at the estuary of the River Lee and is susceptible to tidal, pluvial and fluvial flooding. In 2009, river flooding caused severe damage and disrupted critical infrastructure services, cutting off main transport routes and potable water supply for approximately 87,000 people for two weeks. Within the initial scoping study of the resilience assessment, resilience of critical infrastructure to fluvial flooding was identified as a major issue.

The following stakeholders were identified: The Office of Public Works is responsible for flood management at the national level while the County and City Councils are responsible at the regional and local levels. Managers and operators of critical infrastructure, such as transport networks, utility services, emergency services, hospitals and the university, were invited to the process along with local authorities and first responders.

The resilience of critical infrastructure was assessed using the CIRCLE tool in a workshop setting where attendants mapped locations of Critical Infrastructure (CI) and provided flood impacts and impact thresholds before and after the 2009 event. The assessment demonstrated the effectiveness of building resilience through flood protection, emergency management, and preventing secondary impacts through safeguarding potable water production and power supply assets by highlighting the reduction in the number of disrupted person days: the number of people disrupted multiplied with the duration of disruption. Finally, the study also engaged a committee of relevant stakeholders, who continue to maintain and enhance resilience.

Strengths and weaknesses

Strengths	Weaknesses
▪ Potential to inform policy and investment ▪ A comprehensive assessment of all aspects related to coping with disturbances can be made. ▪ Resilience assessments provide significant information unavailable through alternative assessment forms, such as recovery, indirect effects including cascading effects of the failure of critical infrastructure, and non-tangibles/ non-availability of critical services such as schools and hospitals, and it requires a systems approach (de Bruijn *et al.*, 2018).	▪ Challenging and complex to implement. ▪ Definition of resilience is not universal, creating confusion and inconsistencies when assessing resilience. ▪ The link between indicators and resilience is occasionally weak or indicators overlap or show contradictory results. ▪ Many indicators are only proxies of resilience. ▪ Many frameworks are hazard and/or sector specific. ▪ Indicators are based on informed assumptions of how the system and its components may respond in the case of a disturbance. ▪ Most frameworks provide information for a single point in time.

Suitability for rapid assessment

For local and regional assessments, the accessibility of input data depends on the local data availability and resilience data is not part of European climate data platforms such as Copernicus. As such, a resilience assessment cannot be rapidly conducted. Depending on the scope and method of stakeholder engagement, the process of conducting a resilience systems analysis may take several months (OECD, 2014).

Research gaps

The indicators used for resilience assessment frameworks are often proxies for resilience and limited by the type of accessible and available data. There is also no standardised quantification method or framework.

Model / tool research gaps include:

- A common definition of resilience (of whom and to what) is not available.
- Greater integration with decision-making methods, for example, cost-effectiveness analysis.
- The incorporation of a time dimension within resilience assessment frameworks would aid the design of dynamic adaptation pathways which have a time horizon of several decades.

Finally, without a standardised definition of resilience across contexts, it is challenging to compare different frameworks.

Chapter 2.0: Sectoral models for impact and adaptation assessment

Climate hazards can impact multiple sectors that provide essential services to society, the environment and economy. Modelling the impact and response of these sectors to climate events, such as the impact of flooding on urban areas, supports the tailoring of adaptation strategies to reduce the negative consequences. The model groups detailed in this section typically use outputs from the previous chapter on hazards, their extremes, exposure and vulnerability as inputs. Examples of these sectors include, but are not limited to, tourism, agriculture, and ecosystems and biodiversity.

2.1 Water supply

While drought hazard models quantify drought hazard with a probability, impact models aim to predict the consequences of these drought events on water supply.

Users and application

End users are:

	European	National	Local/Project
Policy and public decision makers	x	x	
Investment, finance and insurance.	x	x	
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	

These impact and adaptation models and tools can support the policy cycle at:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

Model and tool methodology

There are two groups of methods for impact and adaptation analysis: indices and models. An index is a measure for the system performance under given conditions and are often based on geographical data, such as land use maps, and other system characteristics including reservoir storage. Models aim to represent the physical processes, such as water flow and hydropower generation, and human actions, such as dam operation and irrigation, within the system and thus potentially attain greater accuracy than indices. Changes to the system, such as the construction of a reservoir, a diversion canal or irrigation systems, or the different operation or usage of the system infrastructure, such as a different reservoir operation scheme or irrigation, can be tested within a model. Consequently, models are suitable to evaluate or compare adaptation measures. Indices do not usually capture enough detail for the evaluation of adaptation measures, although some indices can be used to evaluate high-level measures to some extent though, such as increasing reservoir storage capacity or growing different crops.

The model approaches can be further categorized in water resources management and agriculture and livestock models. Water resources management models usually comprise of different water use functions and thus address multiple sectors, for example, domestic water supply, industrial water supply, hydropower production and agricultural use. The physical principle of mass conservation, formulated as water balance equations, is the basis of most water resources management models. Agricultural and livestock models are limited to the farming sector, yet they provide a detailed representation of relevant processes, such as crop growth in dependency of moisture.

Indices

Indices have generally been developed to assess socio-economic impacts, however, they have also been applied to the farming sector.

The Multivariate Standardized Reliability and Resilience Index (MSRRI) (Mehran *et al.*, 2015) is a hybrid index consisting of Inflow Demand Reliability (IDR), a top-down drought hazard index for hydrological and socio-economic drought, and the Water Storage Resilience Indicator (WSR), which constitutes a bottom-up socio-economic drought impact index. MSRRI balances the water inflow to the system (IDR) and storage in reservoirs (WSR) with the water demand, providing information regarding the overall condition of the system in terms of hydrological and socio-economic drought. A modification of reservoir volume as a high-level adaptation measure could be captured with this index.

The Water Requirement Satisfaction Index (WRSI) (Verdin & Klaver, 2002) is an index for drought impact on the agricultural sector. It can be used to monitor crop performance during the growing season, which is influenced by the volume of water available for crops measured through a ratio of actual to potential evapotranspiration. These ratios are crop specific and are based on crop development and known relationships between yields and drought stress. A high-level adaptation measure that could be evaluated with this index is the change in crop patterns.

Another index for drought impact on the agricultural sector is the Agricultural Stress Index (ASI, Rojas *et al.*, 2011). The ASI integrates the Vegetation Health Index (VHI) both temporally and spatially. The temporal averaging of the VHI assesses the intensity and the duration of dry periods occurring during the crop cycle at pixel level. The second step determines the spatial extent of drought events by calculating the percentage of pixels in arable areas with a VHI value below a certain threshold value.

Water resources management models

Water resources management models are primarily used for sectors that depend on water and are best applied at the catchment scale rather than for single countries. Multiple software products for water resources management modelling are available on the market.

RIBASIM (River Basin Simulation Model) (van der Krogt, 2010) is a generic water allocation model package for analysing the behaviour of river basins under various hydrological conditions. The model package is a comprehensive and flexible tool, which links hydrological water inputs at various locations with the water-users in the basin. RIBASIM contains crop models, hydropower production and water allocation rules, as well as reservoir operation concepts and can include groundwater resources. A typical use case of RIBASIM is the evaluation of different measures, such as the construction of a dam or a diversion channel, in relation to the balance between water demand and allocation. As part of Deltares' strategy to make its software packages open source, a new scalable version is under development intended for global, regional and local studies. It provides a network representation of water availability, demand, infrastructure, distribution and priority rules for water allocation globally.

E-Water Source[44] is a river basin and catchment modelling platform with three primary modes of execution: catchment, planning, and "river operations". It provides a wide range of model components similar to a rainfall-runoff model, a nutrient and sediment generation and transport model, a groundwater interaction model and a crop water use model. Water management rules include water sharing rules (water governance), resource allocation and environmental flow requirements. E-Water Source can be used for mapping the drought risk to a population, to municipal and industrial water requirements, to agriculture and livestock and hydropower. It was designed initially as Australia's national hydrological modelling platform but has since been used in different countries including India, China, United States and the United Kingdom, among others. A free public version of the tool is available.

The Water Evaluation And Planning system (WEAP) (Johnson *et al.*, 1995) is a software tool for integrated water resources planning. It operates on the principle of a water balance model that can be applied to municipal and agricultural systems, a single watershed, or complex transboundary river basin systems. WEAP simulates a broad range of natural and engineered components within these systems, including rainfall runoff, base flow, and groundwater recharge from precipitation; sectoral demand analyses; water conservation; water rights and allocation priorities; reservoir operations; hydropower generation; pollution tracking and water quality; vulnerability assessments and ecosystem requirements.

An integrated hydrologic model, GSFLOW (Groundwater and Surface-water FLOW) (Markstrom *et al.*, 2008), was developed to simulate coupled ground- and surface-water resources in watersheds through simultaneously computing flow across the land surface and within streams and lakes, as well as within subsurface saturated and unsaturated materials. Climate data consisting of measured or estimated precipitation, air temperature and solar radiation, as well as groundwater stresses, such as withdrawals, and boundary conditions, are the driving factors for a GSFLOW simulation. The model is appropriate for evaluating the effects of land-use change, climate variability, and groundwater withdrawals on surface and subsurface flow for watersheds.

Agriculture and livestock models

The agriculture and livestock models aim to compute the yield of the agricultural sector under hydro-meteorological conditions and farming practices.

CROPWAT 8.0 (Smith, 1992) is a computer program for the calculation of crop water and irrigation requirements based on soil, climate and crop data. In addition, the program supports the development of irrigation schedules for different management conditions and the calculation of scheme water supply for varying crop patterns. CROPWAT 8.0 can also be used to evaluate farmers' irrigation practices and to estimate crop performance under both rainfed and irrigated conditions. Subsequently, CROPWAT models the impact of drought on agriculture and livestock.

[44] https://ewater.org.au/products/ewater-source/

AquaCrop (Saxton & Rawls, 2006) simulates the yield response of herbaceous crops and livestock to water and is particularly relevant under conditions in which water is a key limiting factor in crop production. AquaCrop balances accuracy, simplicity and robustness. To ensure its wide applicability, it uses a limited number of explicit parameters and predominantly intuitive input variables that can be determined using simple methods.

Input data

The input data for the index-based methods varies according to the specific method. The input data for the Multivariate Standardized Reliability and Resilience Index (MSRRI) are hydrological conditions (inflow to the system), water demand and reservoir parameters including storage volume, dead storage and the type of the reservoirs (within-year or over-year).

The Water Requirement Satisfaction Index (WRSI) requires hydrological conditions of rainfall and evaporation, land use, crops and crop-specific parameters.

Agricultural Stress Index (ASI) requires the Vegetation Health Index, which again requires the moisture and thermal conditions.

Water resources management models require input data on the river network; hydrological inflow to the system and evaporation from open water; reservoir parameters such as storage volume, relationship between volume and surface area and relationship between volume and water level; basic operational principles of the reservoir operations (lower and upper rule curve); water demand including extraction points, quantity of water demand, return flows and priorities for water allocation; hydropower production demand and parameters of the hydropower plants such as plant capacity (admission, generation limits) turbine efficiency and parameters to compute the head difference (tailwater level for reservoirs and average head difference for runoff-river power plants).

Output

Indices, water resources management models and agriculture and livestock models highlight the impact of drought on society in general or for specific sectors with an emphasis on the farming sector. A typical water resources management model output computes the degree of a water shortage for all use functions in the system in relation to different sectors and yield loss estimates for farming and reductions in hydropower production. Agricultural and livestock model output is the agricultural or crop yield. These results could be used to evaluate a range of adaptation measures against the degree of water shortage and inform further drought risk analyses or other subsequent indicators for, for example, environmental impact and social impact analysis.

An example case study is the Yangon Urban Services Improvement Project (2019), where the modelling was performed by Haarlem Hydraulics and Deltares as part of a larger ADB funded project led by SUEZ. Yangon is the largest city and main economic hub of Myanmar and the capital of the Yangon Region. The primary water resource for this region is the Ngamoeyeik Reservoir. With the support of the RIBASIM water resources management model, both the existing conditions and likely future climate scenarios with changes in irrigation water requirements were evaluated. The results indicated that under current conditions, no water shortages are expected occur. Under climate change conditions, no water shortages are also expected. However, due to reservoir sedimentation and the increase of water demand for irrigation with the expected increase of farming area (both system changes), water shortages can be expected in the future. Recommendations from the study are to investigate different operation options, irrigation rehabilitation and to agree on shared priorities for water usage among the stakeholders.

Strengths and weaknesses

Strengths	Weaknesses
Index-based impact approaches provide a quick overview of drought impact on various sectors, population or the overall economy. **Water resources management models and agricultural models** simulate processes and operations within the system on a physics-base model and thus provide a greater degree of accuracy compared to index-based approaches. They can be used to evaluate infrastructural measures and operational measures for climate change adaptation as well as provide an input for cost-benefit analysis.	**Index-based impact approaches** cannot be used for the evaluation of adaptation measures. The accuracy is lower compared to models. **Water resources management models** require detailed data regarding the present and planned infrastructure and water demand and are limited to water resources management related sectors. The models often solely compute impact in relation to water supply and not the impact of the shortage on society or the economy. **Agricultural models** also require detailed data regarding agricultural patterns and are limited to the farming sector.

Suitability for rapid assessment

Index-based impact approaches can be used for rapid assessment. The ASI, for example, is computed in real-time by multiple platforms. Water resources management and agricultural models are not directly suitable for rapid assessment predominately because of the greater input data requirements than the index-based approach. If the model is prepared beforehand, a water resources management model could also be used for rapid assessment.

Research gaps

The model approaches are limited to one or a small number of water-related sectors, and typical output parameters are water availability related. It would be desirable to integrate the model with models for other sectors, such as ecology, society through population and health and the economy. For example, it would be desirable to examine not only the impact of water shortage on the hydropower output, but also on the industry that depends on the energy supply, considering alternative energy sources.

To support rapid assessment using these modelling approaches, the models must be correctly setup beforehand. Water resources management models are a common tool for strategic water resources planning and therefore a reasonable or good coverage of the world with water resources management models is already established with an increasing number of models are being developed globally within consultancy projects. However, an inventory of global water resources management models or a model platform where models that are available for rapid assessment can be uploaded to, has not been established yet. The Global RIBASIM initiative has initiated this process and aims to create a global water resources management model.

2.2 Agriculture/ crops

Crop Simulation Models (CSMs) simulate crop growth development and yield through mathematical equations as functions of soil conditions, weather/climate, management practices and crop genetic characteristics (Hogenboom *et al.*, 2004).

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

The CSMs are used mainly in three steps of the adaptation policy cycle, which are:

- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

CSMs are used to reproduce and analyse various processes, including changes in the soil carbon concentration, greenhouse gas emissions, plant breeding, resource use and efficiency of water and nutrients, and crop yield. They can also be applied to evaluate the effects of alternative management strategies under different environmental conditions (Mereu *et al.*, 2019), informing policy and decisions on the impacts of climate variability and change on crop growth and production, as well as on the effects of different management practices on crop yield and the environment. The main information and outputs produced are crop growth and production, carbon, water and nutrient balances.

Model and tool methodology

There are several types of crop models that have been developed over the years, ranging from empirical (descriptive) to explanatory models with varying levels of complexity (Rauff & Bello, 2015). They are used to provide information at varying spatial scales, including field, regional and global scales (Ewert *et al.*, 2015).

Empirical models are based on the direct descriptions of observed data, such as climate and historical yields, and use regression equations to estimate crop yield (Siad *et al.*, 2019). These were the first models applied for yield simulations at a large-scale (Basso *et al.*, 2013). Thompson (1986) applied a statistical model to assess climate change impacts on corn production in five Midwestern states of the USA, while Lobell *et al.* (2011, 2013) also used statistical models to determine the effects of increases in temperature on maize yield in the USA. However, these models provide no information regarding the underlying mechanisms (Phakamas *et al.*, 2013) and their applicability is limited to the location and time period in which the models were developed (Basso *et al.*, 2013). Moreover, they have difficulty offering process-level understanding and testing of adaptation strategies (Rosenzweig *et al.*, 2013). Yet, they can provide insights regarding historical influences on past yields, inform other types of models and can be coupled with process-based models to predict out-of-sample responses (Jones *et al.*, 2017).

Alternatively, more complex models, such as mechanistic or process-oriented models, provide detailed explanations of the soil-plant-atmosphere system and include statistical laws and models such as the hypothesis of crop process or mechanism (Lobell & Burke, 2009; Ewert *et al.*, 2015). In these models, the processes are separately quantified and subsequently integrated into the entire system (Hoogenboom, 1994). The explanatory models generally require a significant amount of input data and involve a large number of parameters. They are currently used to inform scientists, farmers, and decision makers as they can be applied as “what if” tools by simulating changing crop management practices to provide answers to a range of questions, including which crop/variety is most suitable for cultivation under specific conditions, or how to manage fertilization, irrigation, tillage and sowing/planting dates.

These models have been continually improved and implemented to include the capability to reproduce and analyse a wide range of phenomena, such as changes in soil carbon, greenhouse gas emissions, plant breeding, resource use and efficiency, ecosystem services, pests and diseases, food security, yield-gap analysis and climate change mitigation and adaptation to support decision making (Challinor *et al.*, 2018; Holzworth *et al.*, 2015). They differ in the level of detail at which the bio-physical processes are simulated, such as phenology, photosynthesis, respiration, transpiration and soil evaporation, and which production constraints are addressed, such as the potential yield and water and nitrogen limited productivity (Ewert *et al.*, 2015). Moreover, most crop models consider the effect of increasing atmospheric CO_2 concentration on photosynthesis and transpiration and water shortage stress. On the contrary, only a few models consider excess water and oxygen deficiency, soil salinity, heat stress effects and impacts related to frost, snow, hail, flood and wind, and pest and diseases (Ewert *et al.*, 2015).

Among the commonly used process-based models are:

- DSSAT software (Jones *et al.*, 2003; Hoogenboom *et al.*, 2019)
- APSIM (Keating *et al.*, 2003; Holzworth *et al.*, 2014)
- EPIC (Williams *et al.*, 1989; Izaurralde *et al.*, 2006)
- CROPSYST (Stöckle *et al.*, 2003, 2014)
- WOFOST (van Diepen *et al.*, 1989)
- STICS (Brisson *et al.*, 2003; Bergez *et al.*, 2014)
- SALUS (Basso *et al.*, 2006).

The majority of these tools are software that includes crop simulation models for different crops and specific tools to simulate different processes, including soil carbon and water balance and photosynthesis, as well as other utilities and application programs.

Generally, crop models frequently adopt an intermediate level of complexity, mixing empirical and mechanistic approaches to reproduce different processes (Di Paola *et al.*, 2015). The currently developed and applied agricultural models differ in their level of complexity, parameter and input requirements, and in their accuracy in predicting system performance (Jones *et al.*, 2017), as demonstrated by AgMIP (Agricultural Model Intercomparison and Improvement Project). Several crop model inter-comparisons projects have been developed of recent, such as AgMIP (Rosenzweig *et al.*, 2013) and MACSUR (Modelling European Agriculture with climate change for Food Security) (Bindi *et al.*, 2015).

Assumptions

Assumptions and limitations of these models include the availability of input data required for model calibration, evaluation and operation, the uncertainty related to parameters and simulation processes. Several studies have explored the uncertainties related to crop model simulations (Asseng *et al.*, 2019; Bassu *et al.*, 2014). Xiong *et al.* (2019) found that the uncertainty arising from crop models was higher than the uncertainty related to the other sources, such as climate, parameterization and management, combined.

Model verification

CSMs models require an appropriate calibration and evaluation before being applied to estimate crop phenology, yield and/or water and nutrient cycles. The calibration and evaluation of CSMs require a Minimum Data Set (MDS) (Boote *et al.*, 2016).

Input data

Statistical models require historical observations of crop yield and climate factors, while process-based models require a complex MDS for model calibration and evaluation in addition to an MDS for the model operation. However, the input data required is dependent on the model structure and the level of detail at which the bio-physical processes are calculated as well as the desired simulated output.

The majority of these models require the minimum weather/ climate data of maximum and minimum temperature, cumulative precipitation and global solar radiation. However, some models can use climate data at different time steps from hourly to monthly or annual values. Some models also include a “weather generator” to reproduce weather data. Further, crop models require atmospheric CO_2 concentration data for the period of simulation.

Other input data are soil data, such as soil type, depth, texture, organic carbon, bulk density, nitrogen and pH; crop data including genotype, observation of phenology, yield and yield components; and management information such as planting and harvesting dates, row space, plants density, fertilization and irrigation amount, method, dates and tillage.

Outputs

Statistical models are predominately applied to simulate climate risk on crop yield. Process-based CSMs are also used to simulate crop grow in response to weather, soil and management conditions and crop/ variety characteristics. The key outputs include biomass growth, leaf area index, evapotranspiration, grain yield and quality, while the key outputs related to soils are soil moisture, soil nitrogen and nitrogen leaching. However, the outputs they produce depend on the model structure and the level of detail at which the bio-physical processes are calculated by the different models.

Several examples of applications of different crop models at various spatial scales are available, predominately focused on the assessment of climate change impacts than on the evaluation of adaptation options. Among the recent studies that include adaptation are:

(1) Feyen *et al.* (2020) whom applied WOFOST spatially distributed routine to simulate the effects of climate change on yield for wheat, grain maize, barley, winter rapeseed, sugar beet and sunflower, and potential adaptation options such as genotype, planting and irrigation to offset climate change impacts in Europe. It was demonstrated that the implementation of simple adaptation measures, such as changing the sowing dates and use of different varieties, have different responses in relation to the crops analysed: for grain maize, the effects of the tested adaptation options are limited and not sufficient to cope with negative impacts of climate change, yet changing varieties may reap a larger beneficial potential for wheat yields (Feyen *et al.*, 2020).

(2) Asseng *et al.* (2019) tested and applied a 32-multi-model ensemble to assess climate change impacts on global wheat yield and quality while evaluating the effectiveness of introducing genotypes adapted to warmer temperatures on crop yield and quality. Their results indicate that the introduction of combined traits for delayed anthesis and increased grain filling rate could be an effective adaptation strategy for wheat yield, increasing global yield in future climate change conditions.

Other examples of recent crop model applications are reported by Holzworth *et al.* (2015): crop models have been used for yield forecasting in the framework of the JRC activities on Monitoring Agricultural Resources;[45] by the USAID monitoring of Famine Early Warning Systems Network;[46] in farm management advisory programs;[47] and recent applications are also reported in the extensive publications cited in the recently released IPCC reports addressing the impacts of climate change of agriculture.

Strengths and weaknesses

Strengths	Weaknesses
Mechanistic or process-oriented models: ▪ provide outputs based on physiology processes, and hence can simulate the soil-plant-atmosphere system in "new" and	**Mechanistic or process-oriented models:** ▪ require a data on a large number of parameters over a broad range of environments, including crop growth, management and soil and

[45] www.mars.info
[46] www.fews.net
[47] www.yieldprophet.com.au; www.agroclimate.org

untested conditions. ▪ support the simulation of different management strategies and their effects as potential adaptation/mitigation measures.	weather conditions, and are more difficult to calibrate. ▪ are generally developed to simulate processes at the field scale. ▪ Due to the large number of parameters, these models require long time frames to complete simulations.
Empirical models: ▪ describe directly observed data and do not require field and management data for model calibration. ▪ are more suitable for larger spatio-temporal scales.	**Empirical models:** ▪ are poorly suited to estimate future climate change impacts because they cannot represent unobserved changes in adaptation management, soil properties, pests and diseases, and the influence of increasing atmospheric CO_2 concentrations beyond the range of historical data. ▪ Their applicability is limited to the location and time period in which the models were developed.

Suitability for rapid assessment

These models, both empirical and descriptive, are not suitable for rapid assessment as they require access to significant quantities of input data for each specific crop system and area prior to application to provide sufficient information for decision making. In particular, process-based models require careful parameterization and evaluation of the areas and processes of interest.

Moreover, as the majority of the existing models have been developed for research purposes and subsequently adapted to address end user requirements, they are challenging for policy and decision makers to use independently of experts (Jones *et al.*, 2017). However, multiple studies that assess the effects of climate change on crops and/or the effects of different adaptation strategies are readily available and can provide information for decision makers at different spatial scales and for a variety of crops.

Research gaps

As reported by Asseng *et al.* (2015), the major knowledge gaps of CSMs include the limited understanding and modelling of the interactions among climate factors, extreme events such as frost and heat damage, sink–source relationships and changes in quality of crop production under climate change. Moreover, the simulation of a wider range of significant factors, such as pests and diseases, phosphorus nutrition, ozone effect, intercrops and complex rotations, and scaling up of models from the field-scale to landscape level, need to be further explored and implemented in CSMs (Antle *et al.*, 2017).

In addition, the majority of crop simulation models are developed to simulate herbaceous annual crops and few attempts have been made so far to simulate perennial tree crops, such as STICS model for grapevine (Garcia De Cortazar-Atauri, 2006), models for olive (López-Bernal *et al.*, 2018), and hazelnut (Bregaglio *et al.*, 2020). Ewert *et al.* (2015) highlight the gaps related to the number of crops and assessment variables modelled, the multi-scale application of crop models, the management practices considered and the propagation of different sources of uncertainty.

Climatic indicators and/or phenological models are generally applied to assess the impacts of climate change on perennial fruit crops. However, these tools do not include the estimation of yield or crop management, and so they have limited applicability to assess adaptation measures.

2.3 Forestry

These models investigate the dynamics of forest ecosystems under various environmental conditions, natural disturbances and anthropogenic management, including the impacts and adaptation responses to climate change and can inform decision making regarding forest growth, carbon sequestration and sustainable management.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).		x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

These models can be applied to assess various stages of adaptation policy and decision making:

- Stage 2: Assessing risks and vulnerability of reduced forest productivity and other forest ecosystem services to climate change
- Stage 3: Identifying valuable adaptation options such as species composition, ecosystem types and management practices that can support and increase forest functioning under changing environmental conditions
- Stage 4: Assessing the outcome of different adaptation options to sustain forest productivity, as well as biogeochemical and hydrological cycles
- Stage 5: Driving implementation of optimal adaptation practices and forest management

There are several key applications of forestry models:

- Examining forest ecosystem dynamics in relation to their structure and functioning, including forest growth and species composition (Grebner *et al.*, 2013; Pukkala, 2018).
- The impacts on changing ecosystem services provisioning, including the hydrological cycle, bio-geochemical cycles and carbon sequestration (Pan *et al.*, 2011).
- The effect of forest management practices, such as thinning and pruning, for sustainable use (Mönkkönen *et al.*, 2014; Montoro Girona *et al.*, 2017).

Forestry models have been developed and used for productivity assessments by forest managers in both the private and public sectors. Additionally, models to evaluate forest ecosystem services are of interest to the public sector from regional to national and EU level. In the context of climate change, these have been widely applied to: 1) mitigation policies through creating a market for Certified and Voluntary Emission Reduction credits; and 2) adaptation practices to investigate changes in tree species composition and ecosystem types that can sustain optimal levels of ecosystem functioning and services. In addition, at both the regional and local scales, these models have been applied to examine optimal forest management practices to maximise forest productivity and increase timber sales. However, there can be conflicting interests when prioritizing either management or adaptation outcomes. Consequently, trade-offs, such as between providing climate services and promoting biodiversity, need to be considered (Luyssaert *et al.*, 2018).

Model and tool methodology

Several modelling methodologies are used to assess the impacts of environmental and climate conditions on forest productivity, as well as suitable forest management practices which promote climate adaptation (Fontes *et al.*, 2010).

Process-based models

Forest dynamics can be modelled using process-based models which explicitly simulate physiological processes such as photosynthesis, transpiration and respiration and account for limiting biotic and abiotic factors and processes which influence long term forest population dynamics, such as establishment, growth, survival and tree mortality. These processes are simulated as a function of environmental and climate conditions, and, as such, process-based models are optimally equipped to understand forest dynamics under changing conditions and how changes in structural parameters alter these functional dependencies. However, it has not been definitively verified as to which processes significantly influence complex forest dynamics and how this could change under future climate conditions, such as with CO_2 fertilization (Braun *et al.*, 2010; Bugmann and Bigler, 2010).

Empirical models

Empirical models are typically based on statistical analyses and relationships significant to forestry commercial management objectives, in particular related to the sustainable management of forestry targets such as timber production and biomass growth (Andrés *et al.*, 2004; Pretzsch, 2009). These models are based on statistical analyses, such as multivariate regressions and Neural Networks, which are applied to key forest structure and tree species composition parameters which are available from forest inventories (Bailey & Ware, 1983; Fang *et al.*, 2001). However, these statistical relationships are often applied with stationary data such as site index curves, and consequently rarely explicitly describe variations under changing climate conditions (Skovsgaard & Vanclay, 2008). Recent developments have applied a dynamic state-space approach, linking some statistical procedures with varying environmental conditions across gradients (Nord-Larsen & Johannsen, 2007), or productivity-environment relationships (Seynave *et al.*, 2008). Furthermore, the combined use of these models with spatial dynamics of environmental/ bioclimate stratification (Soteriades *et al.*, 2017) can help identify adaptability of site index curves to new sites as the climate evolves.

Hybrid models

Hybrid models combine empirical relationships, estimated from inventory data, with deterministic components of ecophysiological processes (Bartelink & Mohren, 2004; Pretzsch, 2009), thus developing environment-productivity functions that can be applied under different climate conditions. There are a range of hybrid models with various combinations of statistical and process models. There are significant knowledge gaps regarding many physical/ physiological processes and data parameterisation, and therefore statistical relationships may provide greater reliability. For instance, morphological ratios from different tree components could be assessed with greater reliability from inventory data (Valentine & Mäkelä, 2005).

Assumptions

Assumptions and limitations of all model groups are based on the reliability of input data and an incomplete understanding of some physiological process that may be significantly responsible for future responses to climate change, such as CO_2 fertilization. Most commercial tree species are often identified with well-known genotypes, whose parameterization and environmental response behaviour are well understood and anticipated. Other tree species may display significant plasticity along environmental gradients which require flexible and more laborious parameterization processes. Forest distribution may incorporate mountainous areas where climate-topography interactions are more complex and therefore more challenging to model, requiring data with high spatial resolution and reliability.

In addition, climate data and projections from GCMs, downscaled with statistical data or dynamically from RCMs, underpin a large degree of uncertainty regarding the response of forestry models.

Model verification

Model verification can use measurements from forest inventories, which are widely distributed across Europe, and long timescale surveys every five to 10 years. However, certain forest structural characteristics, such as Leaf Area Index, Net Primary Productivity and tree cover, can be monitored continuously with remote sensing data, which is easily and freely available for most purposes at a high resolution. In addition, Laser Imaging Detection and Ranging (LIDAR) data can provide information regarding forest structure and vertical biomass distribution, and the quantity and accessibility of free LIDAR data is rapidly increasing.

Input data

Climate data includes outputs from GCMs and downscaled RCMs. Soil data requirements include soil hydrological properties such as soil water retention, porosity and hydraulic conductivity; soil development/ depth and soil fertility in relation to nitrogen, potassium and phosphorus concentrations. Statistical data from forest inventories include structural forest information such as tree age, basal area, species composition and growth measurements to characterize yield growth curves under different management options.

To conduct accurate assessments and policy and decision making, data at the relevant scale are required (Fonderflick *et al.*, 2010) which should contain high spatial resolution data, especially in heterogeneous areas such as mountain ranges.

Outputs

Forestry models primarily quantify forest productivity in terms of timber, biomass and carbon sequestration as a function of multiple environmental factors and changing climate. Further results with Dynamic Global Vegetation Models (see section 2.5 for more information) also provide information regarding the effects on the hydrological cycle in terms of regulation of water flows, biogeochemical cycles of organic matter and carbon sequestration in forest soils, as well as the effect of multiple functional vegetation types for biodiversity.

Forestry model outputs can be used to inform how management options can optimally sustain forest dynamics, productivity and carbon sequestration. For example, the Carbon Budget Model, CBM-CFS3, is an inventory-based model developed by Natural Resources Canadian Forest Service (CFS) that simulates the stand- and landscape-level carbon dynamics of above and below ground biomass, dead wood, litter and mineral soil (Kurz *et al.*, 2009; Kull *et al.*, 2016). The model has been adapted to simulate forest carbon dynamics at EU level, estimate carbon flows in harvested wood products, and as a support to EU legislation such as EU Regulation 2018/841 on the inclusion of greenhouse gas emissions and removals from land use, land use change and forestry in the 2030 climate and energy framework.

CBM-CFS3 parameters are derived from National Forestry Inventories and include age; area and administrative environmental classifiers that provide link to appropriate yield curves; forest composition; specific silvicultural systems such as even-aged high forests, uneven-aged high forests and coppices; and several management types including clear-cuts with different rotation lengths, thinning, shelterwood systems and partial cuttings.

The CBM-CSF3 is a core component of the BIOMASS bio-economy modelling framework to estimate forest wood supply pathways and, after coupling with the Global Forest Trade Model (GFTM) (Jonsson *et al.*, 2018), can model forest carbon dynamics under business as usual scenario and different policies influencing future harvest scenarios. This framework is also integrated into the Forestry Unified System (FUSION) to generates spatially allocated cost-supply curves of forest biomass (Mubareka *et al.*, 2018) and environmental implications of wood-based products demand and supply.

Strengths and weaknesses

Strengths	Weaknesses
Process-based models	
▪ Provides information explicitly derived by simulating physiological processes as functions of environmental and climate data. As such, these models are more idoneous where site conditions fluctuate, and projections of environmental changes require	▪ Can be cumbersome in terms of the number of parameters for different physiological processes. These parameters are also unique for different species, yet these can be easily attained for most commercial tree species. Additionally, these

extrapolation outside of the range of observed data used for calibration. ▪ Outputs can be used to inform a variety of decision-making contexts, with a strong scientific basis including dynamics of heterogeneous forest systems with a degree of species composition which is typical of more natural areas such as mixed stands.	parameters can vary across gradients for the same tree species as consequence of plant plasticity to stress. Several physiological processes also require further research, such as the effect of CO_2 fertilization on water use efficiency, and their long-term dynamics. ▪ The use of these models requires an understanding of the underpinning processes in order to critically evaluate model uncertainties.
Empirical models	
▪ Can provide rapid and reliable assessments of forest growth under different management options. They are particularly applicable at the local scale where environmental conditions are more stable. ▪ Utilise the large availability of data from forest inventories and are familiar to forestry managers. ▪ Some recent applications have been able to link site specific conditions with changing climate, although the effect of these changes is univocal and do not include multiple dynamics arising from climate changes such as the effect on forest fire and pathogens.	▪ Generally, these models do not consider the effect of changing climate but refer to site indices. Although some recent attempts have tried to link site index to climate conditions and transfer predictions across changing environmental gradients, the effect of climate is not dynamically incorporated into these models. ▪ Their outputs are restrained to a few key factors, traditionally in the interests of forestry production and timber sale. Thus, dynamic changes between ecosystem functioning and soil conditions, including fertility, or hydrological regulation, are not typically accounted for.
Hybrid models	
▪ Combine consolidated empirical relationships estimated from inventory data with reliable deterministic components of ecophysiological processes, thus developing environment-productivity functions that can be transferred under different climate conditions. ▪ Utilise both consolidated data and well understood processes and could be implemented over large scale for key outcomes.	▪ There are a wide range of hybrid models with multiple combinations of statistical and process models. Still, complex dynamics between abiotic and biotic factors and multiple effects of climate change are not considered due to uncertainties regarding the nature of these relationships.

Suitability for rapid assessment

Access to significant quantities of data are available through national inventories, while parameterization for physical based models are also available and suited for most commercial tree species.

Research gaps

Modelling of certain physiological processes are still uncertain, data for non-commercial species is often scarce and information regarding the plasticity of certain species is lacking. Thus, rapid assessments with greater certainty and reliability could be possible for common commercial forest species and for even-aged non-mixed forests. Rapid assessment of the effect of extreme events on forest productivity is challenging due to a lack of integration and ability to predict, for example, threshold effects on ecosystem resilience, natural disturbances and anthropogenic management, including the impact and adaptation responses to climate change, and inform decision making regarding forest growth, carbon sequestration and sustainable management.

Under long term future projections, certain forest dynamics may change significantly, as specific factors, such as CO_2 fertilization, may have significant long-term effects which are currently not fully understood. Additionally, the effect of climate in forest environments is often influenced by topography, for which climate data at a high resolution is often required but are not always readily available for rapid assessment.

Further, there is significant variability regarding the reliability and spatial resolution of soil databases at a local to regional scale.

2.4 Fish dynamics

Fish provide over a billion people with their daily required protein intake and more than 250 million people depend on the fishing industry as a source of income (Cochrane *et al.*, 2009) with the fisheries sector directly employing more than 43 million people (Worldfishcenter n.d.; FAO, 2012, Lynch *et al.*, 2016). Fish thus have an integral role in human society. With the increasing evidence of climate change affecting aquatic ecosystems, impacts on the livelihoods dependent on fisheries are likely and significant (Badjeck *et al.*, 2010). Climate change can impact fish populations via direct or indirect pathways (figure 7) and understanding these pathways can support the development of adequate adaptive measures.

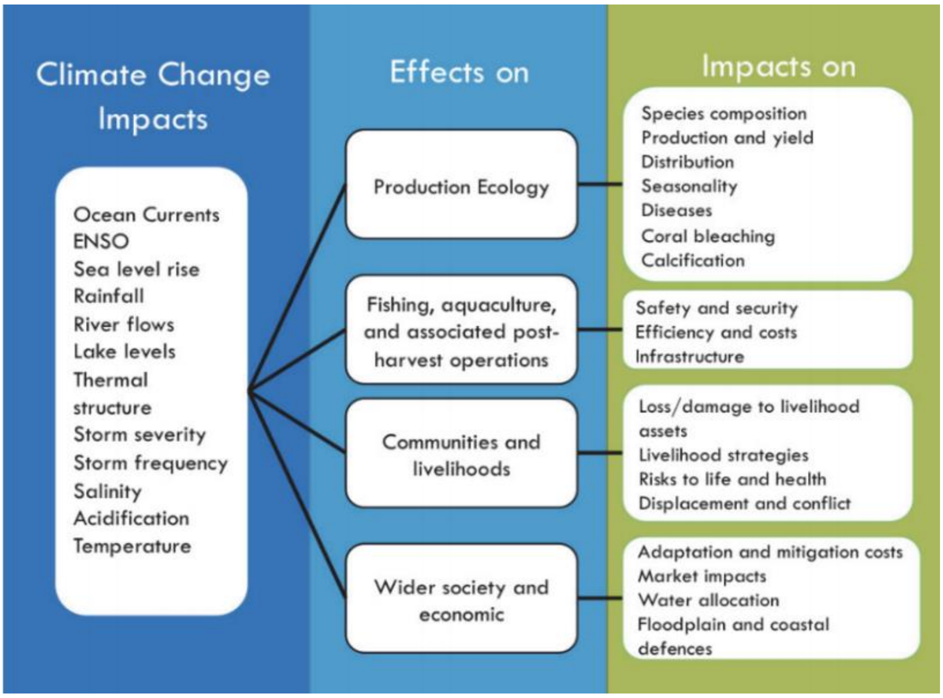

Figure 7: Pathways climate change can impact fisheries and aquaculture. ENSO - El Niño/Southern Oscillation climate phenomena. From Badjeck et al., 2010.

There is a vast array of different types of models and techniques available to predict changes in fish population dynamics. The categories of models assessed are:

- Statistical models
  - Frequentist statistic models
  - Bayesian statistic models
  - Classification models (Boosted regression tree models)
- Mechanistic models
- End-to-End models

Users and application

End users of these models include:

Frequentist statistic models	**European**	**National**	**Local/Project**
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.	x	x	x
Bayesian statistic models			
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.			
Classification models			
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.	x	x	x
Mechanistic models			
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.			
End-to-end models			
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

Adaptation steps	**Frequentist regression models**	**Bayesian statistic models**	**Classification models**	**Mechanistic models**	**End-to-end models**
1. Preparing the ground for adaptation	-	-	-	-	-
2. Assessing risks and vulnerability to climate change	x	x	x	x	x
3. Identifying adaptation options	x	x	x	x	x

4. Assessing adaptation options	x	x	x	x	x
5. Implementation	-	-	-	-	x
6. Monitoring and evaluation	x	x	x	x	x

Models can assess the risks and vulnerabilities of specific fish populations to climate change yet adaptive measures are context specific and require a case by case approach (Shelton, 2014). There are general and practical measures that can help inform policy (Macgregor and van Dijk, 2014). Direct stressors on fish populations can be reduced or removed, such as from (over)exploitation, harmful fisheries practices and sources of pollution. Adaptive management schemes can subsequently ensure sustainable fishing practice, such as by limiting catches based on changes in recruitment, growth, survival and reproductive success (Shelton, 2014). As such, fish population dynamics models can help identify and assess suitable context-specific adaptation options and monitor their effectiveness over time.

Model and tool methodology

Frequentist statistic models

Frequentist statistics is a common tool in studies on population dynamics. For explaining linear relationships, linear regressions can easily be implemented. However, quite often population dynamics demonstrate nonlinear behaviour. In such cases, General Linear Models (GLMs) are strong statistical tools that can manage highly asymmetric and non-normal behaviour of fish related data. General Additive Models (GAMs) are an extension of GLMs and include polynomial terms in their functions. This provides GAMs the greater flexibility to explain erratic data. Regression models (GLM/ GAM) are widely applied to predict changes in fish species distributions. Topics can focus on: ecological and biological system understanding, examining the effects of physical and bio-geochemical interactions and how these impact on fish behaviour, such as predation and mating; fish biology including specific parameters that could instigate migration patterns and fish ecology including predicting habitat suitability under climate change.

Bayesian statistic models

Bayesian statistics are gaining popularity within ecological modelling (Ellison, 2004). In Bayesian statistics, the probability that the hypothesis being tested is true is calculated using the newly sampled and prior existing data. This supports updating probabilities that a hypothesis is true using existing and newly discovered data in contrast to frequentist statistics, where formulation of the null hypothesis is always *de novo*. Thus, the Bayesian method can be used to predict the probability of how populations respond to varying input assumptions, such as habitat conditions. The applicability of this method can also be extended to be used for economical purposes, for example, to predict the likelihood of catches.

Classification models

Although there are numerous types of machine learning techniques, such as Deep Learning and Artificial Neural Networks (section 1.2.4), here the focus is on classification and regression trees (CARTs) and the extension of CARTs i.e. random forest models and boosted regression trees (BRTs). These types of models are becoming more prominent in the field of ecology, as they can appropriately model data that is highly non-linear. Random tree models are extensions of CARTS, as they consist of multiple regression trees that operate together. In such cases, the model's prediction is based on the class that received the most 'votes' from all the regression trees. Finally, BRTs, although not often used in ecological studies, have proven to be superior to most traditional statistical modelling methods in predicting species distributions from occurrence data (Elith *et al.*, 2006; Oyafuso *et al.*, 2017).

Mechanistic models

Mechanistic models implement ecological processes based on key ecological principles, modelling discrete individual fish based on their physiological and behavioural characteristics. The complete life cycle of a fish species can be incorporated into the model. Such agent-based models can simulate the interactions between each individual and their interaction with and responses to the environment.

End-to-end models

End-to-end (EtE) models, or whole-of-system models, incorporate an array of models to represent the entire ecological system. In some cases, these models can incorporate economic systems. Although individual models can differ in their approaches as either mechanistic or statistical, the core principle is that the models are linked so that the output of one model informs the next. EtE models try to include all relevant processes of a system, starting with morphological, hydrological and climatological processes and subsequently informing biogeochemical and finally ecological models (figure 8). When these models also include management modules, the models can also be used to study adaptation strategies.

Assumptions

Frequentist statistics assumes certain structured rules and aligns alternative possibilities in order to identify which ones the data rules out. Bayesian statistics infers rules from collected data and states how probable different possible states are. Machine learning techniques make no assumptions of rules and classify data based on how well it can predict the presented state. The mechanistic approach uses large sets of well documented relationships and devises assumptions based on these. Since end-to-end models consist of set of models, they can be any combination of the above-mentioned models and thus, they will adopt the same assumptions.

Model verification

A commonly used technique in fish modelling is perturbation analysis. This involves testing the model to its extremes using a systematic method: minimizing or maximizing input variables and assessing how this affects different components of the model. This is useful when available empirical data does not cover the time horizon of the forecasts which extends beyond the existing data sets. In other cases, where data sets are large enough, models can be trained with one section of a dataset and verified with another of the same dataset.

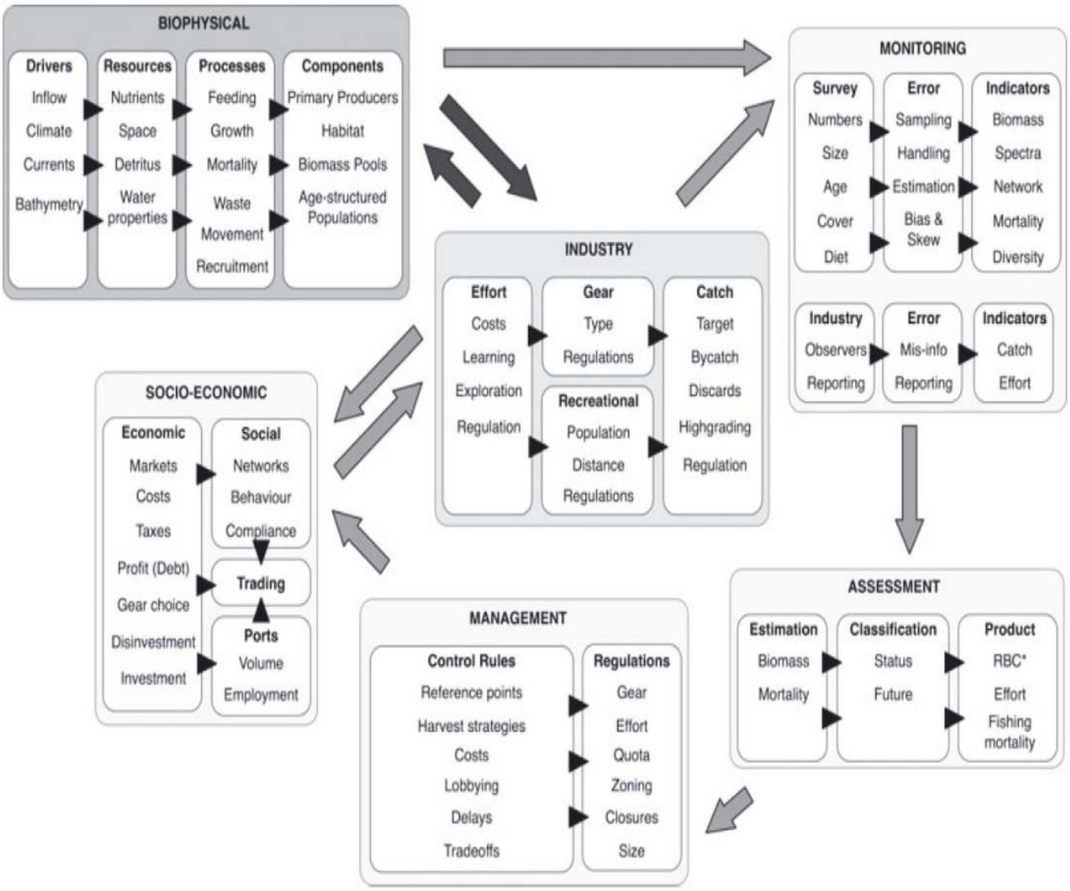

Figure 8: Different systems, sub-systems and their connections in the modelling framework which predict the combined effects of ocean acidification, ocean warming and fishing on marine ecosystems. From Griffith (2012).

Input data

Frequentist regression models: Both GLMs and GAMS use presence/ absence data for spatial modelling of species distributions. The models assume that the current distribution of fish within a geographical area reflects their temperature tolerance. Models require distribution maps of occurrence as well as model predictions regarding future scenarios.

Bayesian statistic models: Bayesian models are able combine different types of input data, such as survey data, crowd sourcing and expert opinions.

Classification models: Classification models can readily manage non-parametric, noisy and missing data. Categorical and continuous variables are both viable options as input. Any type of biotic or abiotic parameter can be used.

Mechanistic models: Each individual fish species has specific traits which can change over time. All of these traits can be used as input data: spatial location, physiological traits, behavioural traits, reproduction, habitat preference, foraging dispersal and energetic budgets. The strength of this model is that it can vary these traits per individual and throughout their life cycle.

End-to-end models: A series of different types of models that interact and can incorporate a range of models such as hydrological, climatological, morphological, biological, ecological and economic models. Each individual model requires a range of data, encompassing a wide range of abiotic and biotic parameters and societal and economic data.

Outputs

Frequentist regression models: In frequency statistics, models aim to relate biotic and abiotic parameters to qualities of fish populations, such as biomass, absence/presence or species richness. Examples include how water temperature can be a strong predicter for fish growth or how fragmenting river connectivity affects fish distribution (Imsland *et al.*, 2005). Venables and Dichmont (2004) examined within which mathematical boundaries GLMs and GAMs are still successful at predicting population dynamics for fish. They found that once models start to go outside the boundaries derived from the data, issues such as variance heterogeneity and non-normality start to play a greater role.

Bayesian statistic models: Bayesian statistical models express the likelihood of a specific quantity of a fish population can occur. For example, they can make predictions regarding fish population size, such as "there is a 90% probability the fish stock is between 1200 and 2000 tons" (Connor *et al.*, 2019). Alternatively, they can express the likelihood of fish catchability at a specific locations using specific equipment, or be used to predict the chances of catching a fish based on its size. (Harley and Myers, 2001).

Classification models: The most common output is in the form of spatial maps which use underlying parameters to best predict the presence or absence of a fish (Miller *et al.*, 2014; Lassalle *et al.*, 2010). For example, Lassalle (2010) was able to predict which areas in the Western Palearctic have a high chance of occurrence of the European Atlantic sturgeon. They achieved this using abiotic parameters as input for the model of summer precipitation, annual air temperature, average slope and marine provinces.

Mechanistic models: The model is built using a bottom-up approach by including individual fish behaviour in the model. Thus, predictions of fish habitat preference are based on their behavioural interactions. See Ayllón *et al.* (2019) and Pinnegar and Polunin (2004). Ayllon uses underlying biological and ecological principles to predict how the Mediterranean brown trout (*Salmo trutta*) will likely react to climate change. The article concludes that under warmer temperatures, many rivers are no longer viable habitat for trout populations and that the effect of climate change is age dependent in which older trout are greater affected.

End-to-end models: The output is presented in the form of habitat preference maps for fish species. Furthermore, it can also deliver predictions on the effects of climate change on the fishery sector. See Fulton (2010), Griffith *et al.* (2012), Lam *et al.* (2016), Christensen and Walters (2004) and Shin and Cury (2001). For example, Griffith examines the individual and additive effects of overfishing, ocean warming and ocean acidification on fish population biomass. The results showed that individually, only ocean acidification had a negative effect on total biomass. However, when fishing was incorporated, ocean warming and ocean acidification significantly negatively affected fish biomass.

Strengths and weaknesses

Models rarely incorporate biotic processes with only mechanistic models explicitly doing so. Therefore, other models relate parameters without accounting for ecological theory.

The non-stationarity of ecosystems is a reoccurring issue for the modelling of ecological systems. That is, ecosystems are in a constant state of flux as genetic structures, evolution, biodiversity and environmental shifts can occur. Therefore, current system behaviour is not always an indicator of how it might behave in the future.

Ease of use and documentation is an important factor that limits the applicability of models. Models are complex and require both an understanding of complex ecological theories as well as a basic understanding of statistics, mathematics and software programming. This can be challenging for non-technical users.

Model type	Strengths	Weaknesses
Frequentist regression models	▪ Most common type of model used, and thus a large body of literature is available.	▪ Rarely does data meet the requirements of independence, homoscedasticity, and multivariate normality.
Bayesian statistic models	▪ Can use any type of data as input. ▪ Can be used for ecological and economic purposes.	▪ Is not often used, and thus has a limited, albeit growing, track record.
Classification models	▪ Has some of the strongest and most accurate predictive capabilities. ▪ Relatively easy to interpret.	▪ Requires significantly large data sets.
Mechanistic models	▪ The only type of model that inherently incorporates biological principles. ▪ Allows for phenotypic plasticity, i.e. it accounts for the non-stationarity of a species.	▪ Requires detailed understanding of how an organism behaves within its environment.

End-to-end models	▪ Can be used for ecological and economic purposes. ▪ Can clearly identify climate change effects on fish populations and the fishing industry.	▪ If underlying models contain errors or large uncertainties, each progressive model will potentially amplify these errors. ▪ Requires vast quantities of data.

Suitability for rapid assessment

Due to the complex nature of fish models and requirements to understand both the technical and theoretical aspects of modelling, rapid assessment is not easily applicable. It is best to involve experts at the early stages of a project life cycle and consult experts to help identify potential adaptive measures. Experts are the only qualified people to deploy models and interpret their results, with or without other stakeholders.

Research gaps

Information and data gaps include the specific effects of climate change on fish species as each species will react differently to climate change. This information could be used to update models with regards to the physiological limitations of an organism.

Most models also do not account for the indirect effects of climate change: a decrease in a population count of one species could benefit the presence of another. Models could therefore be updated to account for such effects. Further, large scale effects of climate change on biodiversity are not fully understood. Yet given that biodiversity is a good indicator for a resilient ecosystem, models could be developed to incorporate how the overall effect of a decrease in biodiversity could subsequently affect fish populations.

2.5 Ecosystems and biodiversity

These models map the adaptation responses of ecosystems and biodiversity to climate change, informing decision making regarding biodiversity conservation management strategies and natural resource use.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

These models can be applied to assess various stages of adaptation policy and decision making:

- Stage 2: Risks and vulnerability of habitats and species to climate change
- Stage 3: Identifying adaptation options
- Stage 6: Monitoring and evaluating the effectiveness of adaptation strategies (Reed *et al.*, 2002).

There are two key applications for ecosystem and biodiversity models:

- Species and habitat conservation management strategies (Mokany and Ferrier, 2011)
- Impacts on and changing provisioning of ecosystem services, including impacts on natural resource industries (Lavorel *et al.*, 2011).

However, there can be conflicts of interest if subsequent human adaptation strategies prioritise either biodiversity conservation or ecosystem services over the other (Chan *et al.*, 2006; Maxwell *et al.*, 2015), and consequently both require simultaneous consideration.

Model and tool methodology

When modelling and assessing climate impacts on adaptation responses of biodiversity and ecosystems and subsequent conservation management strategies, there are several assessment methods (Bellard *et al.*, 2012):

Species distribution models

Species Distribution Models (SDMs) predict future species' distribution patterns in response to climatic parameter projections under GCM and RCM scenarios (Sinclair *et al.*, 2010). Modelling species' spatial adaptation responses to climate change can indicate the magnitude of climatic impact on biodiversity, as well as inform decision makers on potentially important future locations for protected areas (Sinclair *et al.*, 2010) and appropriate human adaptation responses, such as adapting fishing governance in relation to changing fish migration routes (McIlgorm *et al.*, 2010). SDMs constitute the dominant form of biodiversity modelling (Bellard *et al.*, 2012) and are most frequently used to support decision making (Dawson *et al.*, 2011). Examples include species climate envelope/ niche models (Pereira *et al.*, 2010; Bellard *et al.*, 2012), and Dynamic Global Vegetation Models (DGVMs) (Pereira *et al.*, 2010). DGVMs provide integral information regarding the impact of climate change on ecosystem services, as vegetation types fundamentally determine ecosystem service provisioning and regulation (Pereira *et al.*, 2010). Examples of DGVM models include MIGRATE (Collingham *et al.*, 1996).

Species diversity models

An alternative approach to assessing biodiversity and ecosystem climatic adaptation strategies is to examine species diversity in a defined area (Pereira *et al.*, 2010) as biodiversity adaptation responses do not exclusively manifest through dispersal: life history, microevolution rates and interspecific interactions can also change (Maxwell *et al.*, 2015). Modelling changing in situ ecosystem compositions can inform local/ regional impact and adaptation assessments (Pereira *et al.*, 2010), while larger scale species diversity models, such as GLOBIO3, can assess human-induced impacts on species abundance (Alkemade *et al.*, 2009). These responses can be captured utilising species diversity models and indices (Cousins, 1997).

Species extinction risk/ levels

A third climate impact assessment measure of interest to conservation managers are species extinction levels/ risk. Commonly used models include Population Viability Analysis (PVAs), such as Vortex, which are able to test the theoretical effectiveness of conservation management strategies (Lacy, 1993). Use of extinction levels/ risk may be a weaker indicator of climate impacts due to time lags between changing climatic conditions and species' extinction (Dawson *et al.*, 2011), with extinction representing only the final stage of a species' decline (Bellard *et al.*, 2012). Further, extinction level/ risk is a less robust indictor of the impacts on ecosystem services (Pereira *et al.*, 2010).

Assumptions

Assumptions and limitations of all these model groups are based on input data requirements (Lewis, 2006; Sinclair *et al.*, 2010; Dawson *et al.*, 2011), parameter uncertainties (Peterson, 2006) and degrees of error (McMahon *et al.*, 2011).

Model verification

Biodiversity and ecosystem models can use paleoecological records to verify model accuracy and sensitivity through simulating historical species responses to climatic changes (Dawson *et al.*, 2011), as well as provide insights regarding how species may respond to future climatic events (MacDonald *et al.*, 2008). Open source databases, such as NEOTOMA, provide paleoecological records for pollen, plant microfossils, vertebrate and insects (MacDonald *et al.*, 2008).

Input data

Climate data and scenarios from GCMs and RCMs underpin the degree of response modelled in biodiversity and ecosystem adaptation projections (Loarie *et al.*, 2009), providing a fundamental basis for their outputs. In addition, empirical and statistical data and/or biological knowledge to simulate mechanistic relationships are required inputs for these models (Pereira *et al.*, 2010; Mokany and Ferrier, 2011; Bellard *et al.*, 2012).

To support policy and decision making, understanding of ecological, economic and social impacts at the relevant scale are required (Fonderflick *et al.*, 2010). As such, in addition to the pure biological modelling described here, other models and tools required can include economic assessments, valuation tools and socio-economic models of human climate adaptation responses (Preece and Jones, 2002; Kareiva *et al.*, 2007; Maxwell *et al.*, 2015).

Outputs

These models can predict species and biome range shifts and changing ecosystem compositions. For example, DGVMs project that some vegetation biomes could shift their distributions greater than 1km per year (Loarie *et al.*, 2009) and around 40% of Europe could experience greater than 50% of loss of local species by 2050 (Bakkenes *et al.*, 2002).

These outputs can be used to inform both conservation and business management strategies, such as predicting future impacts to agricultural (Fonderflick *et al.*, 2010) (section 2.2) and fishery industries (McIlgorm *et al.*, 2010) (section 2.4). For example, the agricultural grassland regions of Causse Méjan in the French Mediterranean uplands were threatened with tree and shrub encroachment (Fonderflick *et al.*, 2010). Modelling impacts of four agricultural management policies on 60 key species through projected changing habitat composition indicate that strategies which include grazing pressure provide the greatest opportunities for these key species, while also suppressing the threatening encroachment onto agricultural land (Fonderflick *et al.*, 2010).

Strengths and weaknesses

Strengths	Weaknesses
Species distribution models	
Provides graphical output of species range shifts which are accessible to a non-specialist reader.	Either use statistical *or* biological mechanistic inputs and rarely both. Therefore, predicted range distributions may be over/ underestimated.
Outputs can be used to inform a variety of decision-making contexts, including species conservation and human management for resource use.	Assumes climate is determining factor of range distribution, which at a local/ regional scale may not be as relevant.
Species diversity models	
Can provide a localized indication of impacts on ecosystems.	May over/underestimate population persistence due to varying strength of habitat specificity among species.
Extinction risk/ levels - PVA	
Can test the theoretical effectiveness of conservation management strategies	Less robust assessment on impacts on ecosystem services.

based on supporting varying life history parameters.	

Suitability for rapid assessment

Access to significant quantities of data are required through detailed surveying prior to decision making. Once this information is collated, then these models could support rapid assessments.

Research gaps

There is a significant lack of data regarding:

- life histories of species (Pereira *et al.*, 2010) and how these interact with climate change to determine climatic tipping points (Doak and Morris, 2010). This, along with greater analysis of species' genetic diversity for microevolutionary potential (Dawson *et al.*, 2011), could provide greater understanding of species' adaptation capability (Keith *et al.*, 2008).
- species which have not been discovered yet.
- complete knowledge of species distributions.
- complete range of parameters and interactions between them which influence species niche requirements (Mokany and Ferrier, 2011).

Biases in data availability favour species which are easy to monitor, such as bird species over aquatic or microbial species (Mokany and Ferrier, 2011). While this favours the accuracy of models towards well-documented species, semi-mechanistic community models, which utilize both empirical data and biological mechanisms, could be applied to these less data-rich species (Mokany and Ferrier, 2011).

Additionally, non-climate factors significantly impact on species distributions and survival rates, such as pollution, land degradation and habitat fragmentation (Bellard *et al.*, 2012): the compounding effect of including habitat fragmentation and overfishing in addition to climate change projected declines in rotifer populations 50 times faster than assessing these threats individually (Mora *et al.*, 2007). Consequently, greater practice of incorporating compounding factors with climate change on biodiversity and ecosystem responses are required (Bellard *et al.*, 2012).

2.6 Energy

The literature on modelling climate change impacts on the energy sector includes two broad approaches: studies examining the physical impacts on a specific energy carrier, energy generation technology or specific energy sector or side of the market (demand or supply); and studies that couple the output of such physical models with energy system models or Integrated Assessment Models (IAMs) (section 3.1) which couple climate, environmental and economic modules, the latter of which is often a Computable General Equilibrium model (CGE) (section 3.2). Since the first strand of the literature consists of climatological, hydrological and agricultural studies, it falls outside the scope of this section. Models in the second strand of literature have usually a broader focus than climate change impacts and adaptation and are designed to assess the implications for the energy sector(s) under scrutiny of a broad range of shocks, typically but not exclusively, related to energy policy. Some of these models include variables/parameters which depend on climatic variables/indicators and hence can be used to capture climate change impacts on the energy sector and related adaptation options.

Users and application

The end users include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	
Civil society and NGOs.			

The models outlined here can support policy making in the following stages:

- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

Energy system models and IAMs are widely used to support policymaking by quantifying the implications of external shocks for the economic-ecology system under scrutiny. In the field of climate policy, they are typically used to assess the socioeconomic implications of mitigation policies and of climate change impacts and related adaptation policies. European energy and climate strategies rely on scenario projections derived using the widely recognised energy models and IAMs.

The information that can be derived from these models depends on the specification of each model, but usually they provide a depiction of the evolution of the energy sector under alternative scenarios, the costs and benefits of alternative policies and the level of uncertainty associated with assumptions and scenarios. They can also provide indications regarding the level of impact on the energy sector through projections of changes in energy demand and supply, energy mix and associated costs. Depending on the features of the economic module included in each model, they can also quantify the impacts on other sectors of the economy that use energy as inputs, international trade and aggregate indicators such as GDP.

Model and tool methodology

As a general rule, physical impacts on the energy supply side are modelled exogenously and then incorporated into the model as variation in the resource stock that is used to generate energy, such as water available for hydropower generation or cooling thermal power plants. On the demand side, climate change-induced variations in energy demand are captured in two ways: energy for heating and cooling is captured by incorporating the number of heating and cooling degree days into the demand functions for heat and/or electricity; and changes in overall energy demand are captured by incorporating long term elasticity in relation to temperature into the demand function for the relevant energy uses.

Assumptions

Models can be grouped according to the main assumptions associated with the system dynamics: some models assume optimizing behaviour by economic agents (optimization models), others assume that variables adjust to keep the system in a dynamic equilibrium (simulation models). Models can also be grouped according to their coverage of the economic sectors: they can accommodate a holistic overview of economic activities, sectors, and economic agents, such as CGE models, or they can focus on a single sector and treat the behaviour of some agents and of the rest of the economy as exogenous, known as a partial equilibrium model. Models have also varying geographic coverage and resolution, and different assumptions regarding technological change, which can endogenously influence the production of goods and services or be treated as an exogenous factor.

Model verification

Models are usually calibrated to a base year. For the initial few years, the difference between observed and projected values can provide an indication of the model’s accuracy and sensitivity. Unfortunately, since the purpose of these studies is to provide an outlook for the medium and long term, validating their performance is impossible. However, a comparison across alternative models and different versions of the same model could be conducted to assess their ability to keep up with scientific progress in relation to the degree of state-of-the-art progress incorporated. Therefore, there is the assumption that an up-to-date model will attain greater accuracy than outdated models.

Input data

In climate change assessments, energy models and IAMs are usually soft-, and more rarely hard-, linked with climate models or to an ensemble of climate models. Therefore, climate simulations are run independently of energy models, resulting in a lack of feedback between them. To assess the climatic impacts on the energy sector, important variables include: those influencing resource stocks, such as precipitation, water availability, wind speed and patterns; those influencing the functioning of energy infrastructure, such as air and water temperature; or energy demand through heating/ cooling degree days (HDDs and CDDs).

The socio-economic data requirements depend on the specific characteristics of the economic component of the model under scrutiny, but in general, a comprehensive economic and location overview in the base year is required. This includes information regarding prices and quantities of goods and production factors, trade flows, financial variables such as savings and interest rates, stocks of capital and natural resources, economically active population and wages. Depending on the model's dynamics, the future trajectory of some of these variables, typically population, energy prices and GDP growth, may be exogenous and hence require acquisition from external sources, particularly, but not exclusively, for partial equilibrium energy and aggregate energy demand models. CGE models may also need to make assumptions about the dynamic pattern of some parameters.

Outputs

Energy system models provide a full description of the energy sector under scrutiny in relation to energy supply and demand, occasionally with a high temporal resolution; load profiles; fuel mix; prices and costs; investments; and, if technical change is considered, the timing of evolution of new technologies. IAMs, particularly if a CGE is incorporated, can additionally provide users with an economic impacts overview in terms of GDP, welfare, shifts in production, demand, GDP of other sectors, trade, and, in some instances, savings and employment. These models are widely used for EU policymaking as well as by Governments of Member States. However, these typically focus on energy or mitigation policies as opposed to adaptation.

Strengths and weaknesses

Strengths	Weaknesses
▪ Energy system models can provide detailed results which can be readily used for planning and policy making without further analysis. ▪ Modelling frameworks are often flexible and can accommodate any spatial resolution or specific sub sector. ▪ IAMs can provide a comprehensive overview of direct sectoral impacts and of the indirect consequences for the wider (national, EU, global) economy.	▪ Computational limitations imply a trade-off between comprehensiveness and computation time/ feasibility: each model excludes potentially important parameters and/or adopts some coarse assumptions. ▪ The greater the complexity of the models, the greater the degrees of error which can promulgate across the modelling network.

Suitability for rapid assessment

Quick access to input data depends on the specific model in use. Energy models usually require adaptation to the research question under scrutiny which can take time and therefore they do not support rapid analysis.

Research gaps

There is minimal research regarding niche technologies, such as wave and tidal power, as well as emerging forms such as solar power. Further, the impacts on energy transmission and coastal infrastructures also require greater research focus. Extreme climatic events, which can impact on energy transmission and distribution and some energy generation technologies, are rarely studied.

Additionally, uncertainty needs to be factored in more systematically into modelling exercises, with development for assessing adaptation policy options. Further, there is limited inclusion of supply-side impacts in IAMs.

With regard to application gaps, the water-energy-food nexus should be explored further. Studies coupling energy-water impacts at the basin level should be replicated and enriched systematically as few studies review the EU holistically. The wider global energy sector is also highly significant through its influence on EU energy markets in terms of its impact on fuel imports, although it could be expected that with decarbonisation this wider influence may decrease considerably.

2.7 Tourism

The research on climate change and tourism sits within four diverse strands:[48]

- **Evaluation through physical changes**: Tourism activities require the availability of physical factors that can be impacted by climate change. For example, snow cover is crucial for mountain winter tourism, water quality for beaches and coral reef health in tropical areas. Climate change could therefore reduce the appeal of destinations for tourism through lower and less reliable snow coverage, algal bloom/jellyfish proliferation, beach erosion due to sea level rise and coral bleaching.
- **Tourism climate indexes:** Indexes designed to identify comfortable climate condition ranges for the enjoyment of tourism activities. If destinations are consistently perceived to fall outside of these climatic ranges, their appeal may reduce and subsequently observe a migration of tourism to alternative destinations. Specific indexes can be computed for various types of tourism in order to capture the relevant comfortable climatic configurations.
- **Demand models:** Demand models include discrete choice modelling, time series analysis and aggregate tourism demand models.
  - Discrete choice studies using hypothetical questions which can be used to infer tourists' opinions regarding the consequences of climate changes in a given location, however, these models are limited in their applicability beyond the study location.
  - Time series analysis primarily explores the preference inference of tourists through their reaction to present and historic weather conditions. These models can highlight the impact of severe and extreme weather conditions on tourism demand, yet they are limited in their direct ability to support adaptation due to their strict local focus.
  - Aggregate tourism demand models develop on time series approaches to incorporate climate variables and derive estimations of future tourists flows and expenditures in response to climate changes. Here, the focus will be on the latter given their greater relevance for adaptation.
- **Inclusion of impacts within an economic or Integrated Assessment Model (IAM)**: Indicators capturing climate change impacts on the tourism sectors as well as results from demand models can inform more general modelling frameworks to assess implications of impacts and adaptation options on the economy/environment system (section 3.1).

Users and application

End users of these models include:

Physical changes	European	National	Local/Project
Policy and public decision makers		(x)	x
Investment, finance and insurance.		x	x
Business and industry (private sector).	x	x	x

[48] The classification proposed for the first three strands draw upon the approach of Rosselló-Nadal (2014)

Research	x	x	x
Civil society and NGOs. (Tourists)	x	x	x
Tourism climate indexes			
Policy and public decision makers	x	x	x
Investment, finance and insurance.		x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs. (Tourists)			x
Demand models			
Policy and public decision makers	x	x	
Investment, finance and insurance.	x	x	
Business and industry (private sector).	x	x	
Research	x	x	
Civil society and NGOs. (Tourists)			
Inclusion into IAMs/economic models			
Policy and public decision makers	x	x	
Investment, finance and insurance.	x	x	
Business and industry (private sector).	x	x	
Research	x	x	
Civil society and NGOs. (Tourists)			

Adaptation steps	Physical changes	Tourism climate indexes	Demand models	Inclusion in models
1. Preparing the ground for adaptation	x	x		
2. Assessing risks and vulnerability to climate change	x	x	x	x
3. Identifying adaptation options	x		x	x
4. Assessing adaptation options	x			x
5. Implementation				
6. Monitoring and evaluation	x			

Quantifiable physical impacts can be used to directly portray the suitability of a given destination for tourism or to estimate a relation with tourism variables, econometrically or through their incorporation in IAMs. The effect of physical impacts on tourist flows is often non-linear and have a weak correlation until a threshold level is reached. In some instances, projections of physical impacts can directly prompt adaptation decisions: projections of snow reliability may elicit the installation of artificial snowmaking facilities, or a modification of the spatial organization of ski slopes.

Tourism-Climate Indexes can be used to provide an indication of the climate comfort of tourists at any given location with high geographic resolution. They can be projected in conjunction with future climate scenarios for a specific destination and/or used to compile detailed maps of tourism climate suitability for the study area.

Demand Models can estimate variation in tourist flows and expenditures in response to changes in temperatures or other climatic variables. They can subsequently support the development of tourism operation business plans and inform policy measures.

Inclusion of these outputs within general models supports the analysis of the effects of climate change impacts on tourism, and in some applications, of the implementation of adaptation options in relation to the whole economic system under scrutiny. This develops policy makers' understanding of the overall economic costs of climate change impacts and the cost-effectiveness of policy measures.

Physical change quantification provides specific indicators of suitability of a given destination for its designated or planned tourist activities, usually presented in a qualitative format in terms of decreasing levels of suitability starting from an optimal range of scores. Tourism-Climate Indexes provide a clear and objective indication regarding the link between climate conditions and attractiveness at any given location, differentiated according to the specific climate preferences of each market segment. They cannot, however, provide direct inference regarding the consequences in terms of tourist flows. Demand Models yield projections of key economic indicators for tourism such as tourist flows in terms of arrivals, departures and expenditures and can distinguish between domestic and international tourism. Including tourism impacts into more general models provides insights regarding various economic indicators such as variations in GDP, welfare, international trade and any indirect impact on the economic sectors covered by the economic models.

Model and tool methodology

Physical changes

Snow reliability indicators are usually based on the availability of a minimal depth of snow cover on ski slopes for a pre-defined number of days, such as 100 days of permanence of adequate snow cover, or at particularly significant moments of the skiing seasons, such as around Christmas. The specific threshold values and of the number of days varies across studies. Projections of snow reliability indicators can be linked with the altitude of ski holiday destinations which reflects the migration of reliable snow-cover areas to higher altitudes as a consequence of climate change. Recent revisions factor in adaptation measures by accounting for the availability of snowmaking systems and the persistence of conditions for their operation in the future (Steiger *et al.*, 2019).

Climate-orientated tourism assessments could also examine other environmental impacts, such as algal blooms through measurements of new algal biomass, concentration of photosynthetic pigment, quantification of the bloom's negative effect or the algae ratio within the microbial community. Coral bleaching can be measured in relation to the degree of bleaching within each colony and prevalence of bleaching, represented as the percentage of colonies affected by bleaching in a given area. Beach surface area can also be an important parameter for coastal tourism.

Tourism-climate indexes

The main framework is the Tourist Climate Index (TCI) (Mieczkowski, 1985). TCI indicators are weighted averages of sub-indicators, with each sub-indicator capturing climate features deemed relevant for the tourist activity under scrutiny. The weights are determined based on expert judgement in earlier works, while more recent studies attempt to estimate weightings empirically. The scores are usually ranked from ideal, the highest value, to unacceptable. For the original TCI, the range is 100 to -30.

Demand models

The Hamburg Tourist Model (HTM) is the most comprehensive and applicable to support adaptation policy making (Hamilton *et al.*, 2005). HTM's simplest formulation estimates two equations for international tourist departures and arrivals for a specific year. The model uses data from 207 countries and a simulation program to reproduce the flows between the 207 destination and origin countries. Subsequently, scenarios of economic and population growth and climate change provide inputs for the model and used to simulate changes in tourism flows over the 21st century. The model was expanded to include demand saturation and to examine the impact of sea-level domestic tourism, expenditures on tourism and length of stay.

Inclusion within general models

Tourist flows and expenditures from the HTM model are included as exogeneous shocks for the market services sector demand and to consumers' income into ICES' (Intertemporal Computable Equilibrium System) CGE modelling framework (Berrittella *et al.*, 2006) to evaluate the economic impacts on the global economy in climate change scenarios at 2030 and 2050 (Bigano *et al.*, 2008). Projections of TCI indexes and of climate value-at-risk, coupled with alternative adaptation options, are applied by ToPDAd to evaluate climate change impacts on beach and mountain tourism respectively. This highlighted the tourism sector's costs across EU regions, using the WEDDA (Weather Driven Demand Analysis) econometric tool box under different climate change scenarios (Damm *et al.*, 2017). Adaptation options which can be considered include maintaining the type of holidays while changing their peak periods to a greater optimal time of year, moving to an alternative destination or changing the types of holidays but maintaining the same destination, for example, mountain holidays without skiing.

Assumptions

Physical changes: Assumptions are specific to each physical impact and each evaluation method and pertain to scientific domain of each methodology applied. They are therefore outside the scope of this section as, for example, beach and water quality indicators are based on the assumption of climate-ocean models, but all assume a causal link between the variation of climatic parameters and the level of each indicator. Coral bleaching is based on marine ecosystem modelling which requires specific assumptions tailored to the ecosystem under scrutiny.

Tourism-climate indexes: Assumptions evolved from the original formulation towards increasing realism, but their common features include: a) tourists' behaviour responses to variation in several climate features which can be captured through sub-indexes and subsequently summarized as a single indicator; b) the weighting system captures the actual relative importance of sub-indexes; c) for more recent versions of such indicators, extreme weather conditions, captured by wind and precipitations, cannot be compensated by otherwise ideal conditions of other sub-indexes, typically temperature.

Demand models: In HTM, simulations are driven by general attractiveness, distance, population, income and temperature. General attractiveness is a calibration parameter, kept constant, and captures all factors influencing destination choice not explicitly included in the model. Population growth directly translates into a greater number of tourists or higher levels of per capita income which supports more frequent traveling. Annual temperature captures climate through two quadratic relationships: cool destinations gain attractiveness and international tourists as they become warmer at the expense of countries which have become excessively warm, while warm destinations become less attractive.

Inclusion within general models: Climate change impacts are captured as exogeneous shocks to economic variables and/or parameters. ICES use changes in tourist flows and expenditures under climate change from HTM as exogeneous shocks respectively to the market services demand and to disposable income in destination countries. In both ICES and ToPDAd, adaptation only effects demand through changes in destination, time of the holidays and type of holidays.

Model verification

Physical changes: Given their basis on physical indicators, the quality of observed data is intrinsically linked to the observational protocols. For projected values, back-casting procedures can support verifying the accuracy with which the observed values can be reproduced by the model.

Tourism-climate indexes: An initial verification method could compare tourism flows and expenditures with TCI scores: generally, these demonstrate clear positive correlations. For adaptation purposes, the test should focus on the ability of the index to capture the variation of attractiveness of the destinations under scrutiny for the time and geographical resolution desired. In particular, the ability to capture variations in the optimal length and dates of the tourism season is crucial for business planning.

Demand models: These can be calibrated to reproduce actual tourism flows in a base year: variable values are set to match observed values of the base year and their ability to reproduce observed transitions in subsequent years can be verified, although this is not possible for long-term projections.

Inclusion within general models: Similar to Demand Models, IAMs are usually calibrated to a base year. For the initial few years, the change between the observed and projected values can provide an indication of the accuracy and sensitivity of the model. Unfortunately, since the principal purpose of IAMs is to provide an outlook for the medium and long term, verifying their accuracy is impossible. However, a comparison across alternative models and different versions of the same model could be conducted to assess their ability to keep up with scientific progress in relation to the degree of state-of-the-art progress incorporated. Therefore, there is the assumption that an up-to-date model will attain greater accuracy than outdated models.

Input data

Physical changes: Snow reliability indexes require temperature and snow precipitation data and geographical orographic information for the ski slopes under review. Socio-economic data requirements include second-generation snow reliability indicators, incorporating snowmaking capabilities which requires information regarding the deployment of snowmaking infrastructure and on planned investments at the locations under scrutiny.

Tourism-climate indexes: The original formulation required: maximum daily temperature and minimum daily relative humidity (%), which combined together yield the daytime comfort index; mean daily temperature and mean daily relative humidity (%) which combined together yield the daily comfort index; precipitation (mm); sunshine (hrs) and wind (km/h). Other formulation such as the Holiday Comfort Index (Scott *et al.*, 2016) include other climate variables such as cloud cover. Weightings can be based on surveys of the tourist population at relevant destinations concerning their attitude towards optimal and excessive values of the climate variables included into the sub-indexes.

Demand models: Although time series models and choice modelling studies can cover a variety of climate variables, the vast majority of the specifications of HTM are usually based on temperature. There have been a few studies incorporating TCI indicators within this modelling framework. Socio-economic data requirements include tourism flows, counts of domestic tourists and tourists' expenditures in the base year. Population and GDP of destination countries are included among the explanatory variables.

Inclusion within general models: These models require information regarding the tourism market in a base year, including tourism flows, tourist stays and expenditures, and baseline macroeconomic data describing bilateral trade patterns, production, consumption and intermediate use of commodities and services, necessary for running the underlying CGE models such as the GTAP database.[49] Temperature data and projections or TCI index data and projections are also required.

Outputs

Outputs for the models include indicators of physical change, Tourism-Climate Indexes indicators, maps portraying their geographical distribution and evolution over time. Demand Model outputs include tourist flows, expenditures and length of stay for each

[49] https://www.gtap.agecon.purdue.edu/databases/default.asp

country projected under future climate scenarios. Inclusion within general models provides changes in tourist flow together with their economic impacts in terms of sectoral and aggregate GDP, impacts on other sectors and trade.

Snow reliability indexes and TCI-based indicators have been included in Copernicus' C3S Tourism.[50] A downscaled version of the HTM model has been applied to Italy to illustrate the vulnerabilities of the Italian Tourist sector within the Italian Climate Change Adaptation Strategy, while EU and international research projects which incorporate tourism models include ToPDAd, CALDAM-ENV Link, HEXE and COACCH.

Strengths and weaknesses

	Strengths	Weaknesses
Physical changes	Feasibility of high geographic resolution, hence these indexes can provide business-relevant information to tourism operators in a given area, improving investment planning and business strategies.	No standardisation regarding the most suitable suit of indicators as these are often dependent on local circumstances. For snow reliability, adequate consideration of snowmaking is still limited in the literature.
Tourism-climate indexes	Simple and quick depictions of the suitability of a destination for tourism activities.	Some inherent arbitrariness in the choice of weightings. For projections, the uncertainty of each variable can cascade down through the sub-indexes to a large compounded uncertainty for the whole index. No direct link with tourist flows and expenditures.
Demand models	Can capture economic indicators relevant for business planning. Global coverage, suitable for downscaling to regional and provincial level. Can capture both push and pull factors.	Underlying databases require updating. Poor coverage of other climatic drivers other than temperature.
Inclusion within general models	ToPDAd includes adaptation options, accounts for multiple impacts, wide geographical coverage, supports the assessment of different tourism activities at the same destination as adaptation options and provides a simulation tool to extract tourism flow projections at the location of interest.	In ICES, the tourism sector is not present per se, but only as a component of the market services sector. Ad-hoc assumptions were necessary to rescale tourism input data to the market service sector. In both frameworks, the options for adaptation are limited.

[50] https://climate.copernicus.eu/european-tourism

	ICES can incorporate multiple impacts, and it is the only model to include both push and pull impacts on tourism within a CGE framework.	

Suitability for rapid assessment

	Physical changes	**Tourism climate indexes**	**Demand models**	**Inclusion in models**
Quick access to input data/ previous studies	NO	YES	YES (studies); NO (data)	NO
Rapid use of models and methods	NO	YES	NO	NO

Research gaps

The literature on physical impact indicators is inconsistent and a consensus regarding the correct approaches to apply to each destination is yet to be firmly established. This is particularly an issue for snow reliability. Some climate change impacts likely to affect tourism, such as biodiversity losses and forest fires, still need to be explored.

Tourist-Climate Indexes are unequal in their abilities and uncertainty of the projections of their climate inputs. They also need to reinforce their relationship with tourists' preferences through use of widespread surveys to determine tourists' attitudes towards specific climate features; the evidence on this is still limited to a few local studies. Refinements are also required for the design and testing of indexes for specific activities. Most applications so far have examined beach tourism, followed by urban tourism, yet coverage of other tourist activities is scarce. Design of specific indexes tailored to individual tourist activities should be further developed in order to greater holistically assess tourism activities.

Demand models have solely relied on temperature as climate-related drivers, mainly due to multi-collinearity issues among climate variables, and there are still only a few studies incorporating composite tourist climate comfort indexes into demand models. Studies incorporating tourism into IAM's/economic models need to enrich the adaptation options considered, particularly on the supply side. The underlying HTM data requires updating, which has implications for ICES model which uses HTM results.

2.8 Cities and urban areas

These models investigate future urban system dynamics, combining climate, energy, spatial planning and socio-economic models to explore the varying degree of impacts of localised climate change in urban environments. This is predominately applied to the urban heat island (UHI) effect. These models can subsequently test the effectiveness of climate adaptation strategies through land use and urban planning policies, such as urban architectural design, blue/ green infrastructure and reflective surfaces on reducing UHI.

Users and application

Users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.			

Urban system models can inform various stages of adaptation policy and decision making:

- Stage 2: Assessing risks and vulnerability to climate change
- Stage 4: Assessing adaptation options

It has been demonstrated that when controlling for climatic conditions, urban morphology and land artificialisation induces UHI and influences its magnitude and extent (Aguejdad *et al.*, 2012; Houet *et al.*, 2016). Increasing ambient temperatures with climate change exasperates UHI both directly and indirectly, increasing emissions and energy consumption through behaviour adaptation changes such as increasing air conditioning use (De Munck *et al.*, 2013). Yet UHI also significantly impacts on public health (see section 2.12) (Health England, 2018) and workers' productivity (Niemelä *et al.*, 2002). Further, elderly people and low-income households are most at risk due to increasing prevalence of underlying health conditions and reduced adaptation opportunities through unequal access to systems such as air conditioning, therefore exacerbating social inequality (Hajat *et al.*, 2014). Consequently, modelling the increasing effect of UHI and subsequent adaptation strategies are imperative for social, economic and environmental sustainability. Cities are also vulnerable under climate change to increasing flooding (sections 1.1.5, 1.1.8 and 1.1.10), drought (section 1.1.2) and storm damage (sections 1.1.6 and 1.1.7).

While the outputs of urban system models depend on the specific combination of individual models applied, they are predominately used to explore how urban parameters, such as socio-economic conditions, urban development and land use patterns, impact on the distribution and magnitude of UHI (Gill *et al.*, 2007; Chen *et al.*, 2011; Masson *et al.*, 2014; Houet *et al.*, 2016). Changing these parameters through urban and land use policies, such as through increasing green space coverage and reflective surfaces or implementing a green belt zone, can highlight their adaptive effectiveness on UHI (Gill *et al.*, 2007; Oleson *et al.*, 2010; Houet *et al.*, 2016).

Model and tool methodology

Due to the complex and interconnected drivers of multiple urban systems, several specialised models are typically integrated (Chen *et al.*, 2011; Masson *et al.*, 2014; Houet *et al.*, 2016).

Urban climate models

RCMs operate at a resolution of around 25-100km, too coarse a resolution for urban climate modelling which is required to reflect localised, neighbourhood-scale variations in UHI within an urban area. Subsequently, downscaling climate models to the local/ neighbourhood/ building level are required, as demonstrated by the Weather Research and Forecasting (WRF) (Chen *et al.*, 2011), land surface models (Grimmond *et al.*, 2010) and Town Energy Balance (TEB) models (Lemonsu *et al.*, 2015). UrbClim is an urban climate model which also supports short-term urban climate forecasts and longer-term climate projections within urban areas to support adaptation policies.[51]

Urban spatial models

Urban geography can be simulated through a number of models such as Urban Canopy Models (UCMs) (Oleson *et al.*, 2010; Chen *et al.*, 2011), geographic expansion models such as SLEUTH (Houet *et al.*, 2016), architectural models such as GENIUS (Masson *et al.*, 2014; Houet *et al.*, 2016) and Geodynamix, which integrates spatial and urban growth modelling within and outside of Belgium.[52] These aim to model urban morphology and represent the range of drivers on urban development and city profiles, such as compact versus sprawling cities (Lemonsu *et al.*, 2015). This in turn impacts parameters affecting UHI such as wind profiles and turbulence (Chen *et al.*, 2011) and inform urban energy models. Coupled with the urban energy models, urban spatial models provide the geographical distribution of UHI across the urban area of study.

Urban energy models

Urban energy models utilise energy flux parameters for horizontal and vertical facets, such as building walls, roofs, roads and vegetation to model urban surface temperatures (Grimmond and Oke, 2002). The land use and urban development patterns for this are replicated outputs of the urban spatial models (Houet *et al.*, 2016). Anthropogenic heat through emissions and activity should also be incorporated, which can be partially informed through outputs from socio-economic models (Chen *et al.*, 2011). The temperature profiles generated provide users with information regarding the magnitude and diurnal fluctuations in UHI. These models can operate either at a single or multiple vertical levels based on their complexity (Grimmond *et al.*, 2010). Examples include Town Energy Balance – Building Energy Model (TEB-BEM) (Masson *et al.*, 2014) and Noah Land Surface Model (Chen *et al.*, 2011).

[51] https://vito.be/en/product/urbclim-urban-climate-modelling
[52] https://vito.be/nl/product/geodynamix-ruimtemodel-vlaanderen

Socio-economic models

Urban demographics, such as population density and age, and economic status such as household income, have significant implications for the distribution and magnitude of urban expansion, activity levels, energy demand and UHI. One such economic model is NEDUM, which in turn provides outputs used by urban spatial and energy models (Masson *et al.*, 2014; Houet *et al.*, 2016).

These groups of models are integrated and create feedback loops, aiming to holistically model urban dynamics (Chen *et al.*, 2011; Masson *et al.*, 2014; Xu *et al.*, 2019). These models can subsequently be used to test UHI adaptation strategies through changing model parameters, such as increasing vegetation land use/ surfaces. These may require additional specialised models, such as patch-corridor matrix models (Gill *et al.*, 2007), but can demonstrate the temporal and spatial impact policies can have on reducing UHI (Skelhorn *et al.*, 2016).

Online open access city adaptation decision support tools

In addition to these models, there are numerous online decision support tools and frameworks for city adaptation policy and decision making. For further information regarding these urban adaptation tools, see section 5.7.

Assumptions

Assumptions include the accuracy of parameter values and degrees of error (Grimmond *et al.*, 2010), which can promulgate across the modelling network (Lemonsu *et al.*, 2015).

Model verification

Model sensitivity and accuracy can be tested independently and combined using historical and observational datasets to calibrate them based on historical urban transitions (Grimmond and Oke, 2002).

Input data

Climate variables for 100 European cities can be found on the Copernicus Climate Data Store, generated using the urban climate model UrbClim[53]. Climate data requirements include time series of surface heat fluxes, wind profiles, moisture and atmospheric momentum data scaled down from RCMs to the local/ building scale to inform the urban energy models (Grimmond *et al.*, 2010).

To support policy and decision making, further economic assessments of adaptation options such as cost-benefit analyses (section 5.1) and multi-criteria analysis (section 4.3) are required. Additionally, trade-offs between adaptation options are important to assess whether, for example, increasing green areas detrimentally increases water demand for vegetation if urban areas are also projected to experience increasing summer droughts and water scarcity (Gill *et al.*, 2007).

[53]https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-urban-climate-cities?tab=overview

Outputs

These models can provide temporal graphs and spatial maps of UHI magnitude and distribution across the urban landscape under review. The resolution is typically 30/60 minutes and 100m – 10km (Grimmond *et al.*, 2010).

Coupling of a global climate model in conjunction with an urban canyon model projected that converting all urban roofs to white reflective roofs decreased the mean urban heat island effect across urban areas globally by 33% Oleson *et al.* (2010). Further, while consideration needs to be taken with regards to the positioning and strategic location of vegetation, increasing mature tree coverage by 5% reduced the UHI effect by almost 1.0°C during peak UHI conditions in Manchester, UK (Skelhorn *et al.*, 2016).

Strengths and weaknesses

Strengths	Weaknesses
▪ Outputs can promote long-term decision making beyond the political governance timescales of four/ five years and cross-municipality collaboration on urban planning (Houet *et al.*, 2016). ▪ Quantifying adaptation strategies to address UHI supports efficient communication and assessment for policy makers (Houet *et al.*, 2016).	▪ Urban drivers are numerous, meaning it is challenging to incorporate all of these into the models. Therefore, drivers and parameters need to be prioritised, leading to the exclusion of some elements (Chen *et al.*, 2011; Houet *et al.*, 2016). ▪ **Urban spatial models:** Model performance favours higher-level buildings and wider road land use patterns, creating inequality in projection accuracy (Giannaros *et al.*, 2018). ▪ **Urban energy models:** Heat fluxes are variable based on human behaviour, building materials, construction quality and time of day. It is therefore challenging to create accurate datasets (Feddema *et al.*, 2015).

Suitability for rapid assessment

Urban models are data intensive, which can be challenging and time consuming to attain, particularly at a local scale. However, once the data is collated and models are established, the models can provide rapid feedback to decision makers.

Research gaps

Research gaps include:

- Local-scale socio-economic and detailed urban land use data.
- Development of socio-economic projections which are not exclusively GDP-orientated.
- Development of methodologies which can be transferrable between cities.

2.9 Critical infrastructure

These models assess the vulnerability and risk to critical infrastructure systems, such as energy, transportation, water, waste, and digital communications. The models and tools developed for critical infrastructure risk assessments can be used to analyse the benefits of climate adaptation measures.

Users and application

The main users are:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	
Business and industry (private sector).	x	x	
Research	x	x	
Civil society and NGOs.	x	x	

Critical infrastructure risk models are primarily used in:

- Step 2: Assessing the risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

They are primarily applied in risk identification studies and, of recent, used in decision-support tools to support prioritization of adaptation measures. The output of these models highlights the damage and risk of climate extremes to critical infrastructure and demonstrate the benefits in terms of avoided losses through implementation of various adaptation measures.

Model and tool methodology

In the climate impact literature, the cost of infrastructure failure is often estimated in terms of monetary values of physical stocks that are damaged or have failed due to direct exposure to a natural hazard (Scawthorn *et al.*, 2006; Meyer *et al.*, 2013). More specifically, the focus is often on the physical impacts to only the directly affected area (Gerl *et al.*, 2016; Battista e Silva *et al.*, 2019). However, neglecting the impacts outside the directly affected hazard area may result in suboptimal investment decisions due to the implicit underestimation of risk. This has resulted in more recent branches in the literature that focus on the cascading impacts through critical infrastructure system failures, which can propagate disruptions outside of the hazard area due to a reduction in infrastructure services and network effects (Koks *et al.*, 2019).

Infrastructure failure analyses generally come under the topics of infrastructure vulnerability, risk and resilience analysis, which are extensively researched topics. For detailed reviews of these topics and studies see Zio (2009), Aven (2011), Yusta *et al.* (2011) and Ouyang (2014). The key focus of these studies has been on representing infrastructure interdependencies (Rinaldi *et al.*, 2001) and measuring failures of one or more interconnected infrastructures in terms of physical network connectivity failure, service flow disruptions and customer impacts (Hu *et al.*, 2016; Pant *et al.*, 2016, 2017; Kelly *et al.*, 2017; Thacker *et al.*, 2017).

More recent tool branches are decision-support tools, such as the Circle-tool[54] (Deltares). These can be applied in a workshop setting to identify key vulnerabilities within and between infrastructure networks. Within workshops, cross-collaboration can be developed between different network owners, stakeholders and authorities/ governments.

Assumptions

Due to limited availability on infrastructure assets and networks, various assumptions are incorporated into risk assessments. Firstly, there is often limited information available regarding the current condition of the infrastructure. Information such as safety design standards to climate extremes, age of the asset and its maintenance level are, however, essential for understanding asset vulnerability. Consequently, these parameters are estimated based on assumptions. Yet application of deep uncertainty methods within analyses can incorporate these assumptions through applying a range of possible values for each parameter. Secondly, freely available infrastructure network data is scarce, often due to safety reasons. The models therefore require parameter value assumptions around the topology and connectivity within the network, as well as occasionally requiring the creation of partial or entire hypothetical networks (Arderne *et al.*, 2020).

Model verification

One of the key limitations of critical infrastructure risk assessments is the limited observed economic loss data. To validate risk assessments, anecdotal evidence and incidental reports can be used (for example, Kwasinski, 2013 and Kemp, 2016). Cooperation with infrastructure suppliers is required to improve the validation of academic modelling approaches.

Input data

To perform critical infrastructure risk assessments for climate extremes, two types of hazard data are required: (i) hazard footprints for given return periods, such as a flood map with a return period of 1/50 for Europe, to estimate the direct risk to individual assets and (ii) hazard event sets to estimate the vulnerability and resilience of the network. Hazard footprints are often freely available, such as LISFLOOD data (Van Der Knijff *et al.*, 2010) for flooding, and WISC (Maisey *et al.*, 2017) for extratropical storms.

To estimate the societal impacts of critical infrastructure failure and the benefits of avoided losses through adaptation, information is needed regarding the cost of infrastructure, the proportion of the population that utilises each infrastructure asset/system and which industries and businesses rely on which assets and networks. This data can be partly extracted from Eurostat, EEA (Corine Land Cover and LUISA maps) and ancillary datasets developed by academics.

[54] https://www.deltares.nl/en/software/circle-critical-infrastructures-relations-and-consequences-for-life-and-environment-2/

The infrastructure asset and network data can be partly extracted from OpenStreetMap, or through the recently developed HARCI-EU dataset[55] (Batista e Silva, 2019). These are primarily individual assets, for example, electricity (sub)stations, water treatment plants, hospitals or clearly visible networks such as high-voltage lines.

Outputs

Studies may provide risk, damage and loss information per infrastructure asset, vulnerability of the infrastructure network, both direct and indirect (through interdependencies) through economic losses or customers/populations affected and the benefits of adaptation through avoided losses.

Forzieri *et al.* (2018) demonstrate that present and future economic losses to critical infrastructure due to climate extremes are highest for industry, transport and energy sectors. Predicted damages from heatwaves, droughts and coastal floods are expected to increase the most in the future, with future losses not incurred equally across Europe: southern and south-eastern European countries will be most affected and, as a result, will likely incur higher adaptation costs.

Strengths and weaknesses

Strengths	Weaknesses
▪ Infrastructure risk assessments provide essential information to determine societal vulnerability to climate extremes.	▪ These tools and methods require significant quantities of input data with detailed information regarding assets and their locations. This is often not openly available.
▪ As an emerging field, rapid development can be expected in this field. Machine learning could provide opportunities to substantially improve data availability.	▪ High levels of uncertainty may create challenges for the interpretation of the model and tool results.
▪ The framework of the infrastructure risk assessment methods and adaptation pathways are similar to established methods used in building or residential risk assessments. This should support risk managers to rapidly understand modelling approaches.	▪ As an emerging field, data collection and risk assessment frameworks have been the emphasis of research to date; greater development of suitable adaptation measures are now required.

Suitability for rapid assessment

For high-level risk assessments, most data are readily available such as through OpenStreetMap and HARCI-EU. However, detailed local risk assessments will require close collaboration with local infrastructure providers which could slow the assessment

[55] https://figshare.com/articles/HARmonized_grids_of_Critical_Infrastructures_in_Europe_HARCI-EU_/7777301

process. While a number of workshop-oriented tools such as Circle are free,[56] they require experts to host.

Research gaps

- Detailed information regarding critical infrastructure asset characteristics.
- Empirical evidence of the vulnerability of different critical infrastructure assets.
- Empirical evidence of the success of adaptation measures for critical infrastructure.
- Cost of adaptation measures.
- Considerable work is still required in the development of models that integrate both asset and wider-economic impacts through cascading network effects, using empirical data instead of stylized theoretical models.
- Assessment of interdependencies between critical infrastructure networks.
- Few readily available applications to be used by decision-makers.

[56] Such as https://ec.europa.eu/jrc/en/grrasp and Black Sky: https://www.eiscouncil.org/Blacksky.aspx (not free)

2.10 Buildings

These models assess the exposure, vulnerability and risk of buildings. They can be used to estimate the risk to climate extremes and the benefits of avoided damages due to adaptation measures such as wet and dry proofing of buildings.

Users and application

The main users are:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	
Business and industry (private sector).		x	
Research	x	x	x
Civil society and NGOs.	x	x	x

Building damage models are primarily used in:

- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options.

They are primarily applied in risk identification studies and can be used in decision-support tools to support the prioritization of adaptation measures. The output of these models can highlight the damage and risk to buildings from climate extremes and can demonstrate the benefits in terms of avoided damages through implementation of various adaptation measures.

Model and tool methodology

There are two main approaches to estimating building damage: raster-based and object-based. In a raster-based approach, high-resolution land-use gridded data can be used to estimate building damage from climate extremes (Alfieri *et al.*, 2014; Jongman *et al.*, 2012; Ward *et al.*, 2017). In an object-based approach, unique building level information is used instead to estimate damages (Koks & Haer, 2020). Traditionally, the raster-based approach is the most commonly used, however there is a recent increase in applications using an object-based approach. This is primarily due the increased availability of building level data through open access national datasets, OpenStreetMap and machine learning approaches.

The physical vulnerability to buildings is commonly represented using stage-damage functions, also referred to as vulnerability curves, which describe the relationship between the potential damage towards exposed elements for different levels of a hazard, commonly water depth in relation to floods. In most studies, only univariate relationships are applied, such as damage related to water depth only. Yet, of recent, there is an increasing body of literature using multivariate approaches to estimate damages as a result of climate extremes such as damage related to water depth and flow speed on multiple characteristics of the asset (Schroter *et al.*, 2014; Amadio *et al.*, 2020).

Building adaptation modelling primarily focus on two types of measures: wet-proofing and dry-proofing of buildings. Wet proofing is a measure that allows water to enter the building but aims at reducing the damaging effects when it does. This can be achieved through various alterations, such as moving vulnerable functions and installations to higher floors or the use of elevated electricity sockets. Kreibich *et al.* (2005) demonstrated that such adaptations reduced the damage to building structure and content by roughly 40–50 % during the 2002 Elbe floods. Dry proofing constitutes preventing water entry. This includes the sealing of openings such as doors and windows, waterproofing the outside wall and installing back stop valves at connection points with the sewer system. Dry proofing walls above a certain inundation depth is counterproductive, as the pressure difference between the flood water and building interior could create structural instability in the external walls, and eventually result in a catastrophic failure.

Assumptions

While the availability of building location data has increased over recent years, there are still gaps pertaining to building-level information. One such gap is the lack of building structure information. This requires assumptions to be made about the structural design of the building. Secondly, building entry elevations are largely unknown, which is important when conducting flood damage assessments. Thirdly, empirical information regarding reconstruction costs are still limited.

Model verification

Due to limited data availability of observed damages of natural disasters on lower admin levels, such as at a region or city level, and insurance claim data, validation of model results is often challenging. On a national-scale, validation is often conducted through the use of disaster loss databases such as EM-DAT[57] and the NatCatSERVICE[58] database.

Input data

To perform building damage and risk assessments for climate extremes, hazard footprints for given return periods are required, such as a flood map with a return period of 1/50 for Europe, in order to estimate the direct risk to individual assets. Hazard footprints are often freely available, such as LISFLOOD data for flooding (Van Der Knijff *et al.*, 2010), and WISC for extratropical storms (Maisey *et al.*, 2017).

To estimate the societal impacts of building damages and the benefits of avoided damage through adaptation, information is required regarding the costs for rebuilding and different adaptation measures in different contexts as well as the level of socioeconomic development within the area of interest. This data can be partly obtained through Eurostat, EEA (Corine Land Cover and LUISA maps) and ancillary datasets developed by academics.

Building data can be extracted from OpenStreetMap or through national datasets. When using a raster-based approach, Corine Land Cover or LUISA are appropriate

[57] https://www.emdat.be/
[58] https://natcatservice.munichre.com/

datasets. Limited information on building stock and building characteristics can be found through Eurostat.

Outputs

Studies may provide risk and damage information per building and the avoided damages because of risk reduction measures.

Kreibich *et al.* (2005) demonstrated that wet-proofing houses reduced the damage to building structure and content by roughly 40–50 % during the 2002 Elbe floods.

Strengths and weaknesses

Strengths	Weaknesses
▪ For most areas of Europe, availability of building footprint data is increasing although some countries, such as the Netherlands, are already complete. ▪ Simple damage assessment which is easy to interpret and flexible to support testing adaptation measures. ▪ A wide variety of adaptation measures have been developed for buildings, of which several are tested through surveys.	▪ Geospatial building type and information data is still limited. ▪ Detailed damage surveys post floods are uncommon. Consequently, models may be based on poor quality or sparse data. ▪ Extensive effort is required to develop detailed inventory databases/ large valuation surveys to achieve sufficient data for each category/building type. ▪ What-if analyses are subjective, resulting in uncertain damage estimates.

Suitability for rapid assessment

For the majority of European regions, most building footprint data is readily available through sources such as OpenStreetMap and national databases including the Dutch Basisadministratie Gebouwen. Building characteristics and building type information is, however, more limited. This requires users to make assumptions or use proxy datasets such as Corine Land Cover to define building type.

There is an increased tendency towards open-access development. Various models are openly available and easy to use, such as the DamageScanner (Koks, 2019). This is expected to improve in the future.

Research gaps

- Incomplete footprint data in several countries around Europe, including Sweden, Ireland and Portugal.
- Local information regarding building characteristics.
- Greater empirical evidence regarding the cost and benefits of building-level adaptation measures.

2.11 Transport

These models assess the exposure, vulnerability and risk of transport networks. They can be used to estimate the risk to climate extremes and the benefits of avoided losses due to adaptation measures.

Users and application

The main users are:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	
Business and industry (private sector).	x	x	
Research	x	x	
Civil society and NGOs.	x	x	

Transport risk models are primarily used in:

- Step 2: Assessing the risks and vulnerability to climate extremes and climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

They are primarily applied in risk identification studies and, more recently, used in decision-support tools to support prioritization of adaptation measures. The output of these models demonstrates the damage and risk to climate extremes for transport infrastructure and can highlight the benefits through avoided losses of implementing various adaptation measures.

Model and tool methodology

Transport risk assessments for climate adaptation can be subdivided into two main branches: assessments which focus on transport assets, and those which focus on the network (Rozenberg *et al.*, 2019). Asset-level risk assessments are traditionally conducted through a raster-based approach, but there is an increased use of object-based approaches over recent years (for example, Bubeck *et al.*, 2019 and Koks *et al.*, 2019). These analyses focus on direct damage assessments of the transportation network, such as different road and railway segments, through the use of hazard footprint data. These assessments are then used to identify the benefits of segment-level adaptation measures (Koks *et al.*, 2019).

Transport risk analyses that focus on the network primarily examine flow disruptions as a result of natural disasters and aim to identify bottlenecks within the transportation system. While applications to assess the feasibility of climate adaptation measures in transport networks have been limited, there is a growing body of work where this has been applied in developing countries. Examples include Vietnam (Oh *et al.*, 2019), Tanzania (Pant *et al.*, 2018) and Bangladesh (Kwakkel *et al.*, 2019). In these examples, national-scale transport network flow models have been assembled to estimate the benefits of asset-level adaptation measures, such as climate-proofing roads, for the national economy.

Assumptions

Due to limited empirical information and existing research on this topic, numerous assumptions are regularly incorporated into the assessments. For an asset-level analysis, assumptions are often required regarding the characteristics of assets due to limited publicly available information such as road width, paved or unpaved roads, number of road lanes, electrification of railways and port characteristics. Additionally, assumptions are also required to determine the cost of adaptation measures. For a transport risk analysis at the network level, network capacity information is often limited or not available. This often requires analysts and modellers to make assumptions regarding the capacity of the transport network and the flow of goods between certain areas, of which this information is limited on a subnational level.

Model verification

One of the key limitations of transport risk assessments is the limited observed loss data. To validate the risk assessments, anecdotal evidence and incidental reports are required. Cooperation with network suppliers is also required to improve the validation of academic modelling approaches.

Input data

To perform transport risk assessments for climate extremes, two types of hazard data are required: (i) hazard footprints for given return periods to estimate the direct risk to individual assets and (ii) hazard event sets, to estimate the vulnerability and resilience of the network. Hazard footprints are often freely available, such as the LISFLOOD data for flooding (Van Der Knijff *et al.*, 2010), and WISC for extratropical storms (Maisey *et al.*, 2017).

To estimate the societal impacts of transportation failures and the benefits of avoided losses through adaptation, data is required regarding the cost of transport assets, number of people using different modes of transport and which industries and businesses rely on which assets and networks. This data can be partially extracted from Eurostat, UN Comtrade, EU-REGIO (Thissen *et al.*, 2016) and ancillary datasets developed by academics. Transport asset and network data can be partially extracted from OpenStreetMap or through national level datasets.

Outputs

Studies may provide risk, damage and loss information per transport asset, vulnerability of the network, both direct and indirect through interdependencies through economic losses or customers/populations affected and the benefits of adaptation through avoided losses.

Koks *et al.* (2019) reveal that approximately 7.5% of all transport assets globally are exposed to a 1/100-year flood event. A cost-benefit analysis suggests that increasing flood protection would have positive returns on approximately 60% of roads exposed to a 1/100-year flood event.

Strengths and weaknesses

Strengths	Weaknesses
▪ Simple damage assessments which are easy to interpret and flexible in testing adaptation measures. ▪ As a result of extensive mapping in OpenStreetMap over recent years, geospatial data of road and railway assets is readily available.	▪ Little public information is available regarding network flows, making it challenging to assess the wider economic impacts of transport failure. ▪ Development of adaptation measures requires significant quantities of local and detailed knowledge of the assets and how they are managed. This is often not readily available.

Suitability for rapid assessment

For the majority of European regions, most transport infrastructure data are readily available, such as through OpenStreetMap and national databases. Asset specific characteristics and flow information are, however, harder to obtain. This requires users to make assumptions and to manage the uncertainties that arise when making these assumptions.

There is an increased tendency towards open-access development. Various models are openly available and easy to use, such as the GMTRA (Koks *et al.*, 2019). This is expected to improve in the future.

Research gaps

- Detailed information regarding transport infrastructure asset characteristics.
- Empirical evidence of the vulnerability of different assets.
- Empirical evidence of the success of adaptation measures.
- Cost of adaptation measures.
- Significant work is still required for the development of models that integrate both asset and wider-economic impacts through cascading network effects using empirical data instead of stylized theoretical models.
- Few readily available applications which can be used by decision-makers.

2.12 Health and heat

The number of daily deaths increases with average outdoor temperature above certain thresholds, and at higher temperatures this can result in a large number of excess fatalities such as during, but not limited to, heatwaves. There are functional relationships that are used to model these impacts in quantitative terms, and these can be extended to examine the potential benefits of adaptation options in reducing them. These adaptation assessments primarily focus on heat alert systems, though other urban options including green space (see section 2.8) can also be examined.

Users and application

End users of these models include:

	European	**National**	**Local/Project**
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.			

These models can be applied to assess various stages of adaptation policy and decision making:

- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

At the European scale, these assessments have been used to raise awareness regarding the risks of heat related mortality with reported impacts and economic costs (for example, Watkiss and Hunt, 2012; Kovats *et al.*, 2011; Ciscar *et al.*, 2014; Kendrovski *et al.*, 2017) which have been used in European adaptation policy and EEA climate reports. They have also been used to assess the potential benefits of adaptation, primarily focusing on heat-alert systems, either at the national or city scale (for example, Hunt *et al.*, 2016; Chiabai *et al.*, 2018; Bouwer *et al.*, 2018). The latter draw on studies of the effectiveness of heat alerts from existing schemes, such as Toloo *et al.* (2013). Some studies have explored other urban adaptation and reductions in heat impacts including green urban space (for example, Kingsborough *et al.*, 2017).

Outputs from the models include the numbers of fatalities, occasionally respiratory hospital admissions, and, if in an extended framework, economic costs based on estimates of the value of a prevented fatality or year of life lost. Assessment of adaptation benefits can also provide outputs in terms of the number of reduced fatalities due to an adaptation strategy, which to date have predominately focused on heat alert systems. These benefit outputs can be used in a separate analysis of options, for example, to investigate the costs and benefits of adaptation, although there are no integrated adaptation models that examine the costs and benefits of adaptation.

There is also an additional literature that considers heat stress, work output and labour productivity. These examine the effects of temperature and humidity (captured through WBGT) above certain thresholds, the impacts on work output and the resulting change (%) in labour productivity, often split into broad types of work such as outdoor vs indoor (Kjellstrom *et al.*, 2009, 2014). Such approaches have been used to estimate impacts on labour productivity from climate change in Europe (Kovats *et al.*, 2011; Gosling *et al.*, 2018) and are often inputs into CGE models (section 3.2).

Model and tool methodology

These studies / models are primarily based on epidemiological studies (time-series regression analysis) that examine correlations between daily deaths and temperature, such as collated in the PHEWE Project in Europe for specific cities (Baccini *et al.*, 2008), or for specific countries (for example, Hajat *et al.*, 2014 for the UK). These provide functional relationships that support consideration for future climate change. These functions are subsequently used in modelling frameworks, along with gridded population data and future climate model projections, to estimate future impacts. Further assessments can examine the adaptation benefits for any measure that can reduce impacts, though this has been primarily targeted at heat alert systems. Costs are generally assessed independently. The exception is the Climate Change and Health Tool produced by the World Health Organisation (WHO, 2013). This tool consists of a document describing the step-by-step methods in conjunction with a manual with an Excel spreadsheet, constituting a visual aid for calculating costs.

While these modelling assessments are frequently conducted, however, there are few specific models that have been produced for these, as in the case of flood or coastal domains.

For labour productivity, functional relationships are also used, derived from empirical studies. There are physiological limits for an active individual: when WBGT rises above certain limits, individuals must either slow down productivity or stop working, otherwise they will become ill from heat exhaustion and other conditions. There are various functional relationships derived from different groups of studies (see Gosling *et al.*, 2018).

Assumptions

Applying relationships from historic observations and functions may over-estimate future impacts. Studies that account for future acclimatization through natural adaptation report lower estimates, with future impact reductions as high as 50% (Watkiss *et al.*, 2012; Kovats *et al.*, 2011). Furthermore, there is limited data on the effectiveness of current strategies such as heat-alert systems and questions over the transferability of effectiveness between cities. Subsequently, adaptation is rarely accounted for.

Further, many existing studies do not fully capture heatwaves and heat island effects (section 2.8), although this is partly due to the availability of such effects from climate model outputs. Analysis is also challenging as local factors that affect actual heat exposure are difficult to consider, including building (indoor to outdoor temperature) and urban design, which can affect the reliability of transferability of functions from one location to another or geographical aggregation, for example, national or larger studies.

When studies progress to valuation, there is significant variation in results depending on the metric and value used for mortality valuation: Value of a Prevented Fatality (VPF) or Value of a Life Year Lost (VLYL), and the assumption regarding the period of life lost, noting that a significant proportion of heat related deaths are only likely to have been brought forward by short periods of time of less than a month, which raises the question of whether a full value of prevented fatality or life year should be used. For adaptation, there is limited data on the effectiveness of adaptation (heat-alert systems) and questions over the transferability. There are also assumptions regarding building design, including overheating potential, any existing cooling equipment (air conditioning) and access to social health care.

Model verification

The relationships used are based on observational data for a range of cities across Europe. It is possible to validate baseline assumptions by examining primary correlations in the study location between temperature and daily deaths, the data of which are now available at a high gridded resolution in Europe to support such analysis. It is not possible to verify future projections, the potential levels of acclimatisation and the robustness of the projections for heatwaves or heat extremes. Data on the validation of adaptation effectiveness have been made for existing heat alert schemes, but it is not clear whether these levels of benefits will remain under future climate change or across changing patterns of heatwaves and extremes.

Input data

Studies typically use daily mean temperature at a high gridded resolution, such as can be attained from EuroCordex, and combined with gridded population data.

Population (gridded), including future population, are important socio-economic data. Some studies use functional relationships that differ with age to reflect a higher vulnerability in older people and these can consider future age structure in assessing future impacts. Some studies include acclimatisation (autonomous adaptation), which is partially a result of physiological and partially behavioural factors, in order to generate assessments with greater realism regarding future impacts which account for changes over time.

For labour productivity, studies generally use daily WBGT and defined threshold levels and combine these with population or labour distributions by area. These will vary with future population, but also on the labour activities, such as the proportion of outdoor and agricultural work.

Outputs

Outputs include the number of fatalities and economic costs with and without adaptation such as heat alert systems. With extended analysis, assessment of the costs and benefits of heat alert-based systems can be conducted.

The most recent impact studies of heat related mortality in Europe estimated 23,135 excess deaths per year due to climate change for 2°C of warming in Europe (Kendrovski *et al.*, 2017). During the period 2071–2099, an estimated 46,690 and 117,333 additional deaths per year was estimated under the Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 scenarios respectively. These were also assessed in monetary terms, and estimated impacts were €11 to 41 billion per year by 2050 for a 2°C RCP 4.5 scenario. Approximately two-thirds of this increase was due to the climate signal alone, and the rest due to socio-economic change, notably population and age increases. The highest impacts were found in the Mediterranean (Cyprus, Greece and Spain) and some eastern EU countries (Bulgaria, Hungary and Romania). Costs are expected to rise significantly in later years with higher warming.

Several studies have explored the potential benefits of heatwave alert systems for reducing mortality under climate change (Hunt *et al.*, 2016; Bouwer *et al.*, 2018; Chiabai *et al.*, 2018). For example, the estimated benefits of establishing warning systems, real-time surveillance of health data and emergency care and visit plans for vulnerable people, are typically assessed to have between 40% and 80% effectiveness in reducing heat related mortality and have high benefit to cost ratios. Hunt *et al.* (2016) found that the marginal benefit to cost ratio, i.e. the additional benefits versus the increase in additional resource costs, led to a high benefit to cost ratio when VPF mortality valuation metric was used, ranging from 10:1 to 30:1 for London by the 2040s, depending on the degree of climate change.

There are a number of studies that have extended this field to include other urban heat adaptation options. Kingsborough *et al.* (2017) estimated the impact of green infrastructure on reducing the risk of heat-related deaths in London. Their findings indicate that large increases in green spaces are needed to significantly reduce heat related fatalities.

Outputs from productivity studies are usually in the form of days lost, % change in labour productivity (by country), or productivity cost.

Strengths and weaknesses

Strengths	Weaknesses
Quantification and valuation of future health impacts of heat from the European to local level. Once developed, these models are quick to run.	Estimates vary based on assumptions regarding acclimatisation and, for monetary valuation, with valuation endpoints. There are also issues of the robustness of transferability between cities.
Supports analysis of benefits and costs of adaptation strategies such as heat alert systems.	Primarily focused on health system adaptation, such as heat alert schemes. Examining the overall heat adaptation options at the city scale presents a great challenge, although

	some analysis of green infrastructure has been undertaken.

Suitability for rapid assessment

It is possible to access previous data quickly and interpret outcomes. It is also possible to use previous impact data for rapid adaptation analysis, for example, by using previous estimates of city-wide fatalities from climate change and indicative estimates of adaptation benefits based on assumed effectiveness. However, to fully assess the impacts requires detailed analysis that relies on in-depth analysis. It is possible to transfer information on adaptation effectiveness from existing studies, including current ex post information on current schemes, however this relies on assumptions over geographical and context specific factors, that may reduce reliability. Rapid models are not available with detailed quantification, although in theory these would not be difficult to establish, and such approaches have been used in some integrated assessment models.

Research gaps

Research gaps include:

- Effects of heat waves and the urban heat island on mortality.
- Effects of the combination of heat and humidity and other factors such as air pollution.
- Morbidity impacts.
- Valuation of mortality, including period of life lost.
- Acclimatisation.
- Effectiveness of adaptation including transferability.
- Web based tools / open access tools/models for health impact quantification and adaptation effectiveness and benefits.

2.13 Health and other climate adaptation models

There are a number of potential health impacts that could arise from climate change and that have been subject to impact assessments and adaptation analysis using quantitative frameworks and models. In addition to heat related impacts (section 2.12) these include:

- Food borne disease.
- Vector-borne disease.
- Air pollution.
- Water-borne disease.
- Extreme events, covering direct and indirect effects (including mental stress).

Users and application

End users of these models include:

	European	**National**	**Local/Project**
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.			

These models can be applied to assess various stages of adaptation policy and decision making:

- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

At the European and national scale, these assessments have been used to raise awareness regarding the risks of climate change on health (for example, Kovats *et al.*, 2011; WHO, 2017), which have been reported in European adaptation policy and EEA climate reports as well as national risk assessments. They have also been used to assess the potential benefits of adaptation and occasionally considered adaptation options or economic assessments.

The outputs from these studies/ models are the numbers of fatalities or numbers of health impacts and, if in an extended framework, economic costs based on estimates of the value of a prevented fatality or year of life lost, or relevant health outcome. These same frameworks can consider the benefits of adaptation as the reduction in health impacts. These outputs can be used in separate analyses of options, for example, to investigate costs and benefits of adaptation strategies or options.

Model and tool methodology

There are a suite of approaches/models for different health endpoints.

Food borne disease

Salmonellosis is a significant cause of food-borne illness in Europe. Salmonellosis pathogens are temperature-sensitive and demonstrate a distinct seasonal pattern of proliferation, peaking during the summer months. Studies using models based on European-wide time-series, with independent control for seasonal variations and long-term trends, provide functional relationships between climate and pathogen outbreaks (Kovats *et al.*, 2004). These functions are subsequently used in modelling frameworks, along with gridded population data and future climate model projections, to estimate future impacts (Kovats *et al.*, 2011). These can subsequently be extended to examine the impact-reducing benefits of adaptation strategies. Costs are generally assessed independently.

Vector-borne disease

Vector-borne diseases (VBDs) refer to infections transmitted through bites from mosquitoes or ticks. These species are sensitive to climatic factors, and consequently climate change could alter their prevalence (range) or occurrence of outbreaks. Tick borne diseases, such as tick-borne encephalitis (TBE) and Lyme disease, currently constitute the greatest disease risks in Europe. There are also increasing risks of mosquito borne diseases, notably malaria, dengue fever and chikungunya, however these risks are considered low given the availability of effective vector control measures in Europe.

These impacts can be modelled using mathematical-biological models. For example, the Liverpool Malaria Model (LMM) simulates malaria parasite dynamics using daily mean temperature and 10-day accumulated precipitation data for both seasonal epidemic forecasting and climate change applications (Emert *et al.*, 2011). Species Distribution Models (SDMs) incorporated into LMM can subsequently be used to examine the effect of climate change on vector, and therefore disease, prevalence. These models review the environmental parameters governing vectors' current distribution and subsequently assume that these parameters represent the full range of suitable habitat. Projections of climatic range shifts can provide an estimation of future distributions (Ostfeld *et al.*, 2015). See section 2.5 for more information regarding SDMs. This can be used in conjunction with GIS data to examine the climatic suitability for vector borne diseases, exploring prevalence changes with climate change, for example, of the spread of TBE across Europe.

Air pollution

Climate change could alter the concentrations of ozone and particulate matter, affecting health impacts from air pollution. There are an existing suite of air quality and health models used extensively across Europe and at the national level. The most widely applied modelling framework in European policy is the IIASA GAINS model,[59] yet there are numerous air pollution modelling frameworks that are used at national and local scales as well that can be applied to examine air quality[60]. These models can often be used to account for climate change effects, for example, by using climate model projections and assessing future air pollution changes. An example is the study

[59] https://www.iiasa.ac.at/web/home/research/researchPrograms/air/GAINS.html
[60] https://www3.epa.gov/scram001/aqmindex.htm

by the IMPACT2C project (2015) which examined the impacts of climate change on the concentrations of ozone and particulate matter. The integrated air pollution and health models, such as GAINS, can assess options to reduce air pollution, and thus by implication changes induced by climate change, as well as costs and benefits of options. However, these are focused on air pollution control options rather than targeted climate adaptation options.

A further risk is from changes in aeroallergens. Climate change could trigger changes in pollen concentration, volume and distribution (Smith *et al.*, 2014), with an associated increase in the prevalence and severity of allergic diseases in many parts of Europe. There are no estimates of these impacts in terms of the effects of climate change and no models available for climate impact or adaptation modelling, constituting a significant knowledge gap.

Water-borne disease

Impacts of water borne disease can arise from extremes affecting water quality and availability of drinking water, such as floods and droughts. There is some evidence that waterborne disease outbreaks in Europe have been associated with heavy precipitation events. However, there are not quantified models for analysis, partly because the chain from climate extreme through to health impact is complex. There is also evidence of water contamination leading to health impacts during recreational activities or via food, notably associated with climate related algal blooms such as from Vibrio spp bacteria.

Risks of extreme events, including mental stress

There are risks of fatalities and injuries from extreme events, including coastal storms and flooding, river flooding and storms. These can be assessed by extending existing flood modelling frameworks (sections 1.1.5, 1.1.8 and 1.1.10) and assessing potential impacts. For example, Kovats *et al.* (2011) extended the DIVA model framework to examine the health impacts and modelled the costs and benefits of adaptation using the same DIVA framework. There are additional risks associated with post event impacts of floods on mental well-being. While there is less evidence in this field, some modelling frameworks have assessed the potential incidence of these impacts using flood model outputs in combination with estimated incidence levels in affected populations. For example, see Hames *et al.* (2012).

Additionally, the Climate Change and Health Tool, produced by the World Health Organisation (WHO, 2013), consists of a document describing the step-by-step methods in conjunction with a manual with an Excel spreadsheet, constituting a visual aid for calculating costs.

Assumptions

The main assumptions with these approaches are the degree to which correlations and functional relationships derived fully capture complex linkages between climate and health outcomes, and the transferability between locations and to future climate change. In many cases, the disease burden depends on relevant policies and existing control measures as well as behaviour. The consideration of adaptation is relatively undeveloped and has focused primarily on existing control measures, of which there is often little information regarding the effectiveness of these actions under climate change.

Model verification

The relationships used are typically based on observational data. It is possible to validate baseline assumptions through using primary correlations in the study location. Verifying future projections, the potential influence of other factors, and the robustness of the projections to multiple climate metrics, currently constitutes a challenge. There is also a lack of data for the validation of adaptation effectiveness.

Input data

Climate data requirements vary with the exact health endpoint, though often these use daily temperature and precipitation data.

Other factors included population (gridded), including future population. For each health endpoint, there are specific socio-economic factors that are important including food treatment and hygiene for food borne disease, vector borne disease monitoring and control and future air pollution concentrations.

Outputs

The outputs of the models are the number of fatalities or the number of major and minor health outcomes. In extended frameworks, or as part of additional analyses, economic costs can also be calculated. Analysis of possible benefits of adaptation from control measures can be assessed with external assumptions and compared to costs, although these are not considered within the modelling framework.

Example outputs include:

Food borne disease: Kovats *et al.* (2011) estimated welfare costs at EUR 36 million/year in the 2020s (A1B), rising to EUR 68 million/year and EUR 89 million/year in the 2050s and 2080s respectively, yet falling to EUR 30, 46 and 49 million/year if a decline in incidence due to better regulation is included. A later study (Paci, 2014) estimated resource costs for hospital admissions and salmonellosis and campylobacteriosis at EUR 700 million in 2041-2070 (A1B).

Vector borne disease: There are some studies of the potential spread of vector borne disease in Europe (Semenza *et al.*, 2018). Climate change has been implicated in the observed shift of ticks to elevated altitudes and latitudes, notably including the tick species that is a vector for Lyme borreliosis and tick-borne encephalitis. Climate change is also thought to have been a factor in the expansion of other important disease vectors in Europe: *Aedes albopictus* (the Asian tiger mosquito), which transmits diseases such as zika, dengue and chikungunya, and Phlebotomus sandfly species, which transmits diseases including leishmaniasis.

Air pollution: The impacts of climate change on air pollution for Europe were assessed in the IMPACT2C project (2015). For ozone, models predict an average increase across Southern and Central Europe due to climate change, though the rate of increase and the economic costs are low. The impact of climate change on particulate matter was found to be uncertain, with positive or negative outcomes depending on the climate model used, with the impacts/benefits potentially be valued at several billion Euros per year. It is noted that decreases in air pollution from air pollution and wider mitigation policies significantly reduce future impacts, thus marginal changes of climate change on future air pollution levels are predicted to be low, certainly compared to the co-benefits of air quality and mitigation policies. Much larger economic benefits arise from mitigation policies in terms of the positive co-benefits on health from reduced pollution (for example, Ščasný *et al.*, 2015). The European Clear Air Package (European Commission, 2013) estimated that 58,000 premature deaths could be avoided, with benefits of around EUR 40-140 billion.

Floods and health: There are risks of fatalities and injuries from extreme events, such as coastal storms and flooding, river flooding and storms. The impacts were estimated for coastal events in Europe, with welfare costs at EUR 151 million per year in the 2050s and EUR 750 million per year by the 2080s (Kovats *et al.*, 2011). These reduce significantly under the E1 mitigation scenario and reduced increasingly significantly with coastal adaptation. There are fewer estimates of the health impacts of river flooding and storms from climate change, though some national estimates exist. There are also potential impacts on well-being, with higher reported incidence of mental illness in those affected. Country level (UK) analyses (Hames *et al.*, 2012) indicate these costs are low when compared to other categories.

Strengths and weaknesses

Strengths	Weaknesses
Quantification of future health impacts of climate change.	Estimates vary based on assumptions. Limits to the geographical and temporal transferability of functions.
Supports the analysis of benefits and potential costs of adaptation.	There is a lack of information regarding the effectiveness of adaptation options.

Suitability for rapid assessment

It is possible to access and interpret historic data quickly. It is also possible to use historic impact data for rapid adaptation analysis, for example, by using previous estimates of health impacts from climate change, and indicative estimates of adaptation benefits based on assumed effectiveness. However, to fully assess impacts requires detailed analysis that relies on in-depth analysis. It is possible to transfer information on adaptation effectiveness from existing studies, including current ex post information on current schemes, but this relies on assumptions over geographical and context specific factors that may reduce reliability. There are no rapid models available though that supports quantification or analysis of adaptation.

Research gaps

Research gaps include:

- Information regarding the impacts and adaptation options for tick borne disease in Europe as well as new vectors.
- Low levels of impact studies and a lack of adaptation studies for water borne diseases; fatalities and injuries from extremes such as floods and storms; mental health, for example, from flooding; and health infrastructure, health services and social care.
- There is a major gap on allergy impacts, including aero allergens such as pollen.
- In general, there has been few adaptation options which have been assessed in quantitative terms, and a lack of information regarding costs and benefits.

Chapter 3.0: Economic models

An assessment of the efficiency of adaptation measures requires an understanding of economic models. Macro-economic models, including IAMs and CGEs, provide top-down, economic-oriented models to inform the choice of adaptation measures or mix of measures and policies, often under substantial and non-reducible, deep uncertainty. Other economic assessments include insurance impact assessments and behavioural economic experiments, which are important for assessing smaller-scale economic strategies to promote the uptake of adaptation measures.

3.1 Integrated assessment models (IAMs)

Integrated Assessment Models (IAMs) are multidisciplinary, multi-region, dynamic optimization models that represent the integrated functioning of the climatic, environmental and socio-economic system in order to account for the whole causal chain and feedback occurring between climatic alterations and economic impacts.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	
Civil society and NGOs.			

IAMs contribute to the policy cycle during:
- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

IAMs are used to perform policy optimization exercises: given the costs and benefits of a range of climate policies, IAMs can suggest the optimal (growth maximizing) resource distribution across different mitigation actions, such as energy efficiency investments and direct emission reductions, adaptation investments and climate change residual damage. The impact of a single climate policy on other policy priorities and economic development can be assessed.

IAMs have been extensively applied in the development of international climate change agreements to study strategic participant incentivisation and sustained engagement, as well as to identify the potential of different carbon market structures and burden sharing rules to promote the desired outcome. Generally, within mitigation policies, IAMs have been applied to assess the role of technological progress, risk and uncertainty, discontinuities such as those originated from catastrophic events, equity and discounting criteria.

IAMs represent complex and dynamic processes, and as such, they simplify the number of sectors, countries and trade considered to a greater degree than in comparison to Computed General Equilibrium (CGE) models (section 3.2).[61] Their output are thus also "aggregated", reporting policy and climate change costs in term of changes in macro-regional GDP, total investment required to support different energy technologies and mitigation actions for decarbonisation, expenditures in (aggregated) adaptation strategies, changes in emission and emission trade and the timing of these changes.

Model and tool methodology

There are two broad typologies of IAMs: "hard" and "soft" linked. In hard linked IAMs, the climate, environment and economy are considered as a unified mathematical system. In soft linked IAMs, individual models are linked to form a network of output-input-output flows.

Hard linked IAMs, such as the RICE model family (Nordhaus and Yang, 1996; Nordhaus and Boyer, 1999), FUND (Tol, 2006), WITCH (Bosetti *et al.*, 2006) and REMIND (Luderer *et al.*, 2015) are dynamic optimization models whose objective is to maximize consumption or minimize total climate change costs in terms of mitigation and adaptation costs and residual damage. Initially, these models focused on mitigation, with the notable exception of the PAGE model (Hope *et al.*, 1993; Hope, 2006), yet recent developments have included adaptation. Within hard linked IAMs, an economic "core", represented by a macroeconomic growth module, interacts with climate through emissions that lead to increases in global mean temperature. Climate interacts with the economy through a climate change damage function that translates temperature increase into GDP losses. Mitigation and adaptation policies are accounted for through feedbacks between dedicated expenditures on climate mitigation/ adaptation strategies and damage reduction. This occurs indirectly, through lower emissions in the case of mitigation, or directly by modifying the relevant parameters of the damage function in the case of adaptation. IAMs feature the possibility to study complex dynamics, such as non-linear reactions, in the climate-economy system and strategic interactions across countries. This is possible as a result of simplifying the relationships between climate and emissions and of the economy to climatic impacts. This simplification originates through the use of reduced-form functions, most frequently used of which are reduced-form climate change damage functions.

Different IAMs incorporate different parameters: some propose more advanced energy modules through richer energy-generation portfolios, or complex investment modules with different typologies of capital inputs, while others include endogenous technological progress.

Soft linked IAMs are modelling frameworks constituted by models from different disciplines, such as climate models, crop growth models (section 2.2), energy models (section 2.6), land use models and CGE models (section 3.2). These models are linked through feedback mechanisms, with the output/input flow across models constituting the "link" which is "soft" as the models remain distinct, in order to capture and represent the whole causal chain from impacts to economic damages. Climate change mitigation and adaptation policies can be implemented in soft linked IAMs depending upon the capacity and characteristics of the models which are part of the framework. Examples of these frameworks include IMAGE (Stefhest *et al.*, 2014), AIM (Kainuma *et al.*, 2003; Fujimori *et al.*, 2012) and SGM (Prinn *et al.*, 1999).

[61] Yet this limitation is diminishing given recent increases in computational power abilities.

Assumptions

Usually, the economic core of hard linked IAMs are exogenous growth models, à la Solow or Ramsey, or endogenous growth models à la Grossman Helpmann. They also assume that countries have perfect foresight decision makers that act rationally with complete information. The climatic core of IAMs constitutes a reduced form of climate models which separate out and simplify in “boxes” the carbon cycle across the geosphere, hydrosphere and atmosphere, producing results comparable to complete climate models. Damages are represented by reduced form functions that translate temperature increases into economic (GDP) losses. These highly aggregated functions are parameterized according to expert opinions and literature surveys.

Model verification

Behavioural parameters of hard linked IAMs are calibrated based on existing data, estimated econometrically or expert opinions. Their economic cores are developed based on consolidated and well-defined theoretical underpinnings. However, given that hard linked IAMs generate future projections, they can therefore be challenging to verify.

Soft linked IAMs are modelling frameworks composed of multiple models. Accordingly, the quality and validation of the framework is dependent on the quality and validation of each model. They also pose an additional requirement: in principle, the feedback mechanisms across the model network is a closed system in which the outcome is required to be unique and stable. In soft linked IAMs, this cannot be verified analytically, but through multiple simulation rounds of the whole integrated structure. Given the high computational requirements to do this, this test is rarely performed.

IAMs, especially hard linked IAMs, have been critiqued due to either a lack of empirical foundation in the calibration of damage functions or for missing key elements in the analysis, such as institutional factors (Pindyck, 2013; Stern, 2013, 2016).

Input data

Hard linked IAMs typically utilise temperature data, aggregated according to the time and spatial resolution of the models, as parameters for the reduced-form climate change damage function. These data are, however, produced endogenously by the models which incorporate reduced-form climate models transforming emissions into temperature. Soft linked IAMs may require a greater number of and different climatic data, depending on the model’s part of the modelling framework.

Hard linked IAMs are dynamic optimization models. Accordingly, they require a set of starting social economic, such as GDP, population and capital stock, emissions data to initialize the simulation and a set of parameters which drive intertemporal model behaviour. They can be calibrated to replicate given emission and socio-economic scenarios, including damages. Mitigation and adaptation modules also require calibration, requiring prior knowledge of costs and policy effectiveness at a given time.

Outputs

Hard linked IAMs are “aggregated”, top-down, multi country optimization models. Consequently, their outputs constitute changes in macroeconomic variables such as the impact on GDP, allocation of expenditure or investment across different “items”, or policy decision variables which enhance objective outcomes. This is usually a global or regional intertemporal utility function that depends upon consumption.

Soft linked IAMs can provide a richer spectrum of outputs stemming from each of the modules composing the modelling framework. Therefore, they can encompass not only socio-economic assessment of impacts and policies, but also environmental and bio-geo-physical impact indicators.

Hard linked IAMs have been extensively used to analyse many different aspects linked to climate change impacts and policies, such as:

- quantification of climate change costs and of the social cost of carbon (Hope, 2006, 2011; Link and Tol, 2011; Nordhaus, 2017).
- the definition of optimal mitigation policies (Nordhaus and Yang, 1996; Popp, 2006; Tol, 2006; Bosetti *et al.*, 2015).
- the costs assessment of given climate policy targets with a particular emphasis on the role of technology (Riahi *et al.*, 2015; Rogelj *et al.*, 2018; Bertram *et al.*, 2018; Kriegler *et al.*, 2018).
- equity issues in climate change policies and strategic incentives to participate to international environmental agreements (Bosello *et al.*, 2003; Heykmans and Tulkens, 2003; Manne and Stephan, 2005; Anthoff *et al.*, 2009; Bosetti *et al.*, 2011).
- the role of discounting (Anthoff *et al.*, 2009; Emmerling *et al.*, 2019).
- the role of different forms of risk and uncertainty in shaping climate action (Gjerde *et al.*, 1999; Millner *et al.*, 2013; Anthoff *et al.*, 2014; Drouet *et al.*, 2015; Markandya *et al.*, 2019).
- the interaction and optimal balance between mitigation and adaptation. In this case, analyses have been conducted to inspect the effectiveness of international financing of adaptation using the revenue from emission trading (Hof *et al.*, 2009), to determine the optimal combination between proactive, reactive adaptation and adaptation capacity building and, more generally, how the presence of adaptation impacts climate change policy (Hope *et al.*, 2003, 2006, 2009; de Bruin *et al.*, 2009b; Felgenhauer and de Bruin, 2009; Agrawala *et al.*, 2010; Bahn *et al.*, 2010; Bosello *et al.*, 2013).

Strengths and weaknesses

Strengths	Weaknesses
Hard linked IAMs: ▪ are mathematically consistent, which enables discussion of the properties of the solutions found, including existence, uniqueness, stability and time consistency. ▪ can guarantee, by construction, that the policy advice produced	**Hard linked IAMs:** ▪ The main critique is their weak empirical foundations upon which climate change damage functions are calculated. This, according to some experts, could undermine the validity of their policy recommendations.

are cost and time efficient. ▪ can analyse complex dynamic interactions across multiple agents and policies. **Soft linked IAMs:** ▪ are flexible, accommodating increasing complexity and realism in the description of the investigated phenomena.	Similar issues occur with the calibration of adaptation cost-effectiveness modules implemented in some IAMs. Both hard and soft IAMs, even though the problem is magnified in hard linked IAMs, can only incorporate a few social dynamics relevant for the assessment of climate change impacts and policy process, such as non-market dimensions, institutional factors or, more generally, sub-optimal situations including limited information, bounded rationality, liquidity constraints.

Suitability for rapid assessment

Hard linked IAMs generally do not have quick access to data, however there is an increasing tendency to offer open source codes of simplified model versions such as the Nordhaus DICE/RICE models,[62] or user friendly websites also enabling non-proficient users to run policy simulation exercises, such as the WITCH[63] policy simulator model (Bosetti *et al.*, 2006).

Research gaps

Hard linked IAMs have been criticized due to the large approximations introduced by their reduced form functions of climate change damage or cost/effectiveness of adaptation functions. Improving the empirical foundations of these functions is thus important to increase the credibility of the tools' recommendations.

IAM models' socio-economic cores are generally still based on standard economic theory. This is typically endogenous/exogenous growth in hard linked IAMs, and often general equilibrium in soft linked IAMs. Therefore, factors that are outside these theoretical boundaries, such as non-market dimension of climate change impacts and institutional barriers, are not readily included in the analysis.

Hard linked IAMs are, on average, aggregated geographically. Therefore, they cannot generate sufficient detail to warrant a credible application for local scale adaptation assessments. At best, they can provide orders of magnitude of adaptation investment for national or EU planners. This limitation could be partially overcome using soft linked IAMs where the existence of different models facilitates reaching higher spatial resolutions. Still, there is a scale mismatch between indications provided by IAMs and support needed for local adaptation action. Additionally, there is a timing issue: often, tailoring and running IAMs to specific conditions requires a longer time scale than ideally required for policy making.

[62] https://sites.google.com/site/williamdnordhaus/dice-rice
[63] https://www.witchmodel.org/simulator/

3.2 Computed general equilibrium (CGE) models

Computable General Equilibrium (CGE) models are single or multi-country, multi-sector economic models. They represent economic systems through markets' functioning: describing how firms and households, and supply and demand 'match' to determine quantities bought and sold and prices. CGE models also describe how these interactions, that substantiate domestic and international trade flows, determine country GDPs and other macroeconomic variables.

Users and application

Users of these models include:

	European	**National**	**Local/Project**
Policy and public decision makers	x	x	
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	
Civil society and NGOs.			

CGE models contribute to:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change
- Step 4: Assessing adaptation options

CGE models have been extensively applied to the study of trade and public sector policies as well as climate mitigation policies, the economic assessment of climate change impacts and to investigate market driven adaptation. However, few studies have tried to assess the effects of planned adaptation. All major international institutions, such as the World Bank, the OECD, the European Commission, the IMF, and national institutions commonly use CGE models as support to policy evaluation.

CGE models quantify macro-economic or "higher order" effects of perturbations in the economic system. For example, they assess how a shock, such as a policy or environmental change, influences sectoral production, prices, demand, country GDP, income, competitiveness and trade once markets have adjusted.

Model and tool methodology

CGE models offer a multi-market and multi-country representation of the economy constituting domestic and international trade. All markets are linked as supply and demand of factors of production, goods and services are sectorial and internationally mobile. These flows are determined by changes in relative prices that signal to optimizing (rational) producers and consumers how to allocate resources efficiently. In this way, CGE models can capture market adjustments triggered by a localised shock onto the global context and vice versa. Notwithstanding these common traits, CGE models can display different features: for example, they can be static or dynamic, single or multi-household, feature perfect markets or market imperfections, or endogenous or exogenous technical changes.

Assumptions

CGE models are typically based on the assumption that markets are perfectly competitive and that agents are perfectly rational, for example, that households and firms behave as if maximising objective, utility and profit functions under constrains. The rationale of this theoretical underpinning are the welfare properties of competitive markets granting an economic efficient/ least cost solution. This can offer a useful benchmark to examine deviations from this ideal set-up. CGE models however are flexible enough to allow for market imperfections and frictions in adjustments. The international trade description of CGE models is based upon the Armington assumption: domestic and imported goods are imperfect substitutes (Armington, 1960). Other more sophisticated trade representations in CGE models includes firms' heterogeneity (Melitz, 2003) that improves their realism in describing dynamics in trade expansions.

Model verification

CGE models cannot be tested with a "standard" process of back casting for validation, where results are verified through a model's ability to replicate the effects of a historic and observed policy intervention. In principle, back casting simulations can be performed (Liu *et al.*, 2004) yet in practice this is rare. The main reason constituting that the impact drivers of an economic shock, such as a policy, or sudden financial or environmental change, are numerous and models can readily fail to capture all of these within its simulation capacity. Eventually, CGE models' results, although quantitative, require interpretation as providing greater qualitative indications and "orders of magnitude" rather than exact figures. This said, CGE models' structure and parameterization are not arbitrary and are calibrated: their data and behavioural relations through, for example, demand, supply and trade, are based upon national accountings and reflect observed market exchanges in a given year. Furthermore, extensive sensitivity analyses on model parameters can be, and are, conducted to understand what, within the models, derives the major sources of uncertainties.

Input data

CGE model databases are derived from Social Accounting Matrices (SAMs), built from national input-output tables, that record domestic and foreign country and sectoral exchanges in a given year. Other key information in CGE models are the elasticity of substitutions in demand and supply that can be either calibrated or estimated econometrically. Furthermore, a typical starting point for a CGE model simulation are policy shocks, such as a tax, subsidy or quota, or, in the case of evaluation of climate-change impacts, a set of physical consequences triggered by climate stressors: for example, lower availability of productive land due to floods or drought; lower labour productivity due to thermal discomfort or health issues; or changes in energy demand for cooling and heating purposes.

In the case of planned adaptation, input data can constitute the costs and effectiveness of the adaptation strategy, for example, how much land loss is avoided due hard coastal protection, when and where. These can subsequently be translated into changes in demand and supply relations in the model that finally produces an assessment of the indirect economic consequences. This implies that relevant input information for a CGE exercise often derives from impact or "bottom-up sectoral" models, such as crop models (section 2.2), sea level rise models (section 1.1.10), energy models (section 2.6) or health care analyses (sections 2.12 and 2.13). The output from these models need to be harmonized with the spatial and time resolution of the CGE models. Often, this requires an aggregation effort as the scale of the impact models is usually a higher resolution than the country or regional scale of CGEs.

There are different sources of input-output data that can form the basis for the construction of global CGE models: open source, such as the World Input/ Output Database (Timmer *et al.*, 2015) and EORA (Lenzen *et al.*, 2013); or commercial, for example the GTAP databases (Aguiar *et al.*, 2019). Building blocks of CGE models are also available for customization to specific purposes, either open source, such as the IFPRI model (Lofgren *et al.*, 2002) or commercial (Aguiar *et al.*, 2019).

Outputs

The outputs of CGE models consist of absolute and/or percentage changes in sectoral production, prices, trade flows, terms of trade, GDP income and the price and quantity variables considered by the model from the pre to the post-shock situation. In the specific case of adaptation, CGE analysis does not suggest which adaptation measures to adopt, neither compute its costs nor its effectiveness. Rather, once the cost and effectiveness of adaptation measures are known, these can be used as an input for the model that can determine the impact of that adaptation strategy on the economic performance of sectors and countries.

CGE models have been extensively applied to the study of mitigation policies (Whalley and Wigle, 1991; Burniaux *et al.*, 1992; Bohringer *et al.*, 2009, 2010; European Commission, 2008, 2010, 2018). Since the end of the 1990s, CGE models have been increasingly applied to the study of climate change impacts (McCallum *et al.*, 2013; Ciscar *et al.*, 2018; Dellink *et al.*, 2019) to determine the indirect or higher order cost of climate change shocks: how impacts influence the capacity of a country to produce GDP, income and competitiveness once markets have adjusted.

This is relevant for adaptation analysis as CGE models can highlight the role of autonomous adaptation that operates through the market forces, known as market driven adaptation. Examples in this vein are CGE assessment of climate change impacts on energy consumption (Ciscar *et al.*, 2011, 2018; Eboli *et al.*, 2010), tourism destination choices (Berrittella *et al.*, 2006; Bigano *et al.*, 2008; Ciscar *et al.*, 2011; Eboli *et al.*, 2010) and health care demand (Bosello *et al.*, 2007; Ciscar *et al.*, 2011; Eboli *et al.*, 2010). In all of these cases, adaptive responses are modelled through forcing household consumption towards specific behaviours such as energy vectors, recreational or healthcare services, and verifying how this demand re-composition affects sectoral and country economic activity. For example, the market response through crop switching has been reviewed extensively (Chalise and Naranpanawa, 2016; Darwin, 2004; Darwin *et al.*, 1995; Fujimori *et al.*, 2018; Reilly *et al.*, 1994). This literature has been reinvigorated by the development of the agro-ecological zone approach supports greater realistic representations of land suitability (Golub *et al.*, 2013; Lee *et al.*, 2009). The CGE literature examining the macroeconomic effect of adaptation options such as irrigation, fertilization or shifts in planting/sowing dates, is less comprehensive.

Some attempts have tried to include public-planned adaptation in CGE models. This is usually modelled as a redirection of resources, for example, of public expenditure toward protection activities. These reduce adverse climatic impacts but displace other investments or private consumption. Adaptation to sea-level rise is a topic diffusedly investigated. Darwin and Tol (2001) and Bosello *et al.* (2007, 2012) use CGE models to estimate the economy-wide consequences of coastal protection. Ciscar *et al.* (2011) include the costs of forced costal migration, which could also be considered a form of adaptation, imposing representative households in the GEM-E3 CGE model distortionary consumption.

The main outcomes highlighted are that direct and indirect climate change costs are different, showing some tendency to be lower, and to be lower than costs estimated with different methodologies (Howard and Sterner, 2017). Even when indirect costs are considered, adaptation can generate greater benefits than its costs (Bosello *et al.*, 2012).

An important issue regarding the information extracted from CGE models which goes beyond the analysis of climate change impacts and adaptation, is connected to the market-based nature of these models. Input data is generated through observed marked transactions and, accordingly, CGEs can measure perturbations that directly affect these. However, losses in non-market goods and services, such as the value lost from biodiversity degradation and any subsequent loss in welfare which could potentially induce changes in consumers' behaviour, cannot be evaluated because an official market for biodiversity, with explicit demand and supply schedules, is not available.

However, this also applies to financial elements. Financial assets are not measured by GDP, and therefore are not captured under the CGE logic. An example of this is highlighted by the PESETA III and IV studies in which the economic cost of health impacts from climate change are assessed using value of statistical life techniques, and not CGE modelling. Yet, the CGE approach could provide information regarding the cost of shifting private and public expenditure toward heath care, however the redistributional economic effects are considered scarcely representative in changes of mortality and morbidity.

Strengths and weaknesses

Strengths	Weaknesses
CGEs constitute one of the few approaches able to represent systemically market driven adaptation and its effect on sectors and countries. Flexibility: in principle CGE models	Due to the "coarse" spatial resolution, adaptation effects can only be assessed across "aggregate" and large areas. CGEs' are unsuitable for the assessment of single adaptation

enable the assessment of higher order consequences of numerous different impacts and policies, including planned adaptation, under the condition that they can be translated into changes in demand and supply of goods and services represented in the model.	measures due to their macro-economic focus, but can assess generic and larger-scale adaptation expenditure. Adjustments within CGEs are usually instantaneous and costless, and therefore transitions costs tend to be underestimated. Given their basis on observed market exchanges, CGEs are not suitable for analysing the impacts and adaptation of non-market goods and services and externalities. Similarly, including financial issues are challenging. As CGEs are deterministic models, the risk dimension, for example, of how high-level damage can impact on economic activity can be challenging to incorporate.

Suitability for rapid assessment

Using pre-existing datasets and models, such as the World Input/ Output Database (Timmer *et al.*, 2015), EORA (Lenzen *et al.*, 2013) or the GTAP databases (Aguiar *et al.*, 2019), although time saving, requires an advanced modelling knowledge. Quick access to input data for adaptation analyses is not available.

Research gaps

Research gaps include the lack of comprehensive, internally coherent and homogeneous import and export data sources, implying international trade relations in global CGE models' databases are always reconstructions of real data.

The typical unit of investigation of CGE models is at the country level, due either to the scale of available social economic data, especially bilateral trade flows, or to the heavy computational burden. Local specificities of impacts, and accordingly of adaptation options, cannot be accurately considered. Some sub-national CGE models exist (Lecca *et al.*, 2018), but they have not been extensively applied yet to impact and adaptation assessments. Improving the spatial resolution of CGE models, through either developing innovative techniques to downscale their results or to couple them to different tools for local impact assessment, could be a useful improvement.

CGE models are based upon national statistics on observed and observable market transactions. Accordingly, they are ill suited to economically assess damages of climate impacts and benefit from adaptation affecting non-market goods and services such as ecosystems, biodiversity and health. Including a non-market dimension in CGE models could be an important step forward.

Finally, CGE models are currently not extensively applied to planned adaptation policy assessments. Further, CGE investigation of the cost of extreme/catastrophic climatic events is stylized, representing the effect of a weighted average damage with weights given by the event probability, rather than considering in full the role of risk and risk aversion.

3.3 Macro-econometric models

Macro-econometric models are multi-country and multi-sectoral forecasting whose relations between the different macro-economic variables are estimated using regression analyses, typically panel or time-series.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	
Investment, finance and insurance.	x	x	
Business and industry (private sector).			
Research	x	x	
Civil society and NGOs.			

Macro-econometric models contribute to:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change

and potentially, although rarely, applied at:

- Step 4: Assessing adaptation options

Macro-econometric models quantify macro-economic effects of public sector policies on GDP, sectoral demand and supply. They have been extensively applied to a range of public-sector policies. In comparison to CGE models (section 3.2), macro-economic models are greater suited to capture market imperfections and introduce external elements of national accounting or the fundamental economy drivers such as monetary and financial dynamics and bounded rationality.

Model and tool methodology

The key feature of macro-econometric models is to parameterize the relationship between variables using time series analysis based on yearly or quarterly data. These amalgamate into complex and integrated dynamic equations which emulate demand and supply. Outputs of these equations are fundamentally determined and validated in relation to historical empirical observations. They are also often categorised as neo-Keynesian given their fundamental basis in Keynesian economics in which the demand side drives the system, and markets may present excess demand or supply. Their empirical derivations support them to consider deviations from "perfect" market conditions with greater flexibility. They often feature, for instance, market power in the energy markets, involuntary unemployment in the labour market and/or money and financial effects. As such, they are often incorporated into modelling toolkits of national central banks and of national ministries of economy and finance.

Assumptions

The fundamental basis of macro-econometric models are structural equations describing agents' behaviour, for instance, of demand and supply systems, which can be based upon differing schools of economic theory. They are subsequently specified into econometric models that are econometrically estimated from large databases. A distinctive feature of macro-econometric models is their neo-Keynesian derivation in which demand-driven shocks are the main drivers of economic changes and may result in markets with excess demand or supply.

Model verification

The quality of macro-econometric models depends initially on the quality and quantity of input data used and the rigour of the estimation process. This currently encapsulates the major strength and weakness of these models. As they are empirically founded, they can represent multiple complex phenomena provided that this is captured within the observed data. For the same reasons, their outputs are only accurate assuming that future trends emulate historical correlations. This is the Lucas critique of the 1970s (Lucas, 1976), even though concerns regarding the stability of parameters estimated econometrically were presented in the 1930s (Frish *et al.*, 1938). Yet, the debate is still ongoing. For instance, see Aufhammer (2018) on the ability to capture adaptation dynamics with econometric techniques.

Input data

Data requirements for the development of macro-econometric models are typically long time series of economic data on national income and product accounting, as well as multiple other variables represented in the structural equations to enable the estimation of behavioural parameters.

Outputs

Overall, macro-economic models are applied to study the effect of policies or other shocks on the economic system (Takeshita, 2004; Pollit and Barker, 2009). The outputs of macro-econometric models are similar to those of CGE models, consisting of absolute and/or percentage changes in sectoral demand and supply, prices, trade flows, terms of trade, GDP income and price and quantity variables considered by the model, from the pre to the post-shock equilibriums. Macro-econometric models have not been applied yet to the study of adaptation, which could be extended to include impact and adaptation equations derived from the expanding econometric literature on this topic.

Macro-econometric models have been widely applied during assessments of environmental tax reforms. A prolific field of research examined the potential to obtain a second dividend/ increased employment in the labour market following a well-designed mitigation policy transferring the burden of the taxation system from labour demand to polluting activities (Bosello and Carraro, 2001; Bach *et al.*, 2002; Barker *et al.*, 2009). They have also been applied to the study of decarbonisation and energy policies (Lutz *et al.*, 2010; Lehmann *et al.* 2018; Knobloch *et al.*, 2018).

Strengths and weaknesses

Strengths	Weaknesses
The major strength of macro-econometric models is their flexibility to account for deviations from perfect market conditions and the possibility to expand the analysis beyond the real side of the economy of monetary and financial dynamics.	Developing a macro-econometric model requires the availability of a significant quantity of high-quality datasets and its process can be complex and computationally heavy. Macro-econometric models, given their derivation on historic data, may not correlate with future long-term trends and, as such, can provide limited accurate information. Notwithstanding the micro-foundation, their macro-nature poses a barrier to their ability to portray micro-economic dynamics.

Suitability for rapid assessment

Datasets are not openly available for macroeconomic models. With the correct access to these, experts could provide rapid analysis, however it can be time consuming to tailor the models to the specific policy questions and scenarios.

Research gaps

Often, the analytical capacity of macro-econometric models is limited by the quality of the available data. It also does not appear as if macro-econometric models have been applied to adaptation assessments yet, but have, in theory, the capability to inform the economic impacts of adaptation strategies.

3.4 Behavioural economics

Behavioural economic methods include surveys and economic experiments regarding individual perceptions of climate change-related risks, such as natural disasters, and demand for adaptation measures including insurance to reduce these risks. Moreover, these approaches examine the factors which influence these perceptions and demand, providing insights into strategies which can stimulate individuals to implement adaptation measures.

Users and application

End users of behavioural economics include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.			

These methods can be applied to assess various stages of adaptation policy and decision making:

- Step 4: Assessing adaptation options
- Step 5: Implementation
- Step 6: Monitoring and evaluation.

Studies have been used to examine the psychological factors which explain perceptions of climate change-related risks and demand for disaster risk mitigation and insurance, such as an individual's physical location, feelings towards natural hazard risks, natural hazard characteristics, and direct experience and knowledge (Bubeck *et al.*, 2012; Robinson and Botzen, 2018). These insights are useful for designing policies aimed at promoting adaptation to climate change risks, such as risk communication (Botzen and van den Bergh, 2012), nudges designed to change the decision environment without altering material incentives (Chaudhry *et al.*, 2018), and policies which alter material incentives with respect to risk reduction, such as insurance premium discounts (Mol *et al.*, 2018).

Model and tool methodology

The main behavioural economics methods applied in this field that inform adaptation policies can be divided into surveys of perceptions towards climate change-related risks, surveys regarding demand for protection measures against climate change-related risks and economic experiments.

Surveys of perceptions towards climate change-related risks

Surveys with regards to perceptions towards climate change-related risks, such as natural hazards, typically involve exploring risk perception variables, such as perceived probability, expected damage and natural hazard characteristics, including expected water levels. Furthermore, individuals may be asked their physical location using postal code to assess objective risks and other factors that could explain risk perception, including cognitive, affective and socio-economic variables. Most recent surveys are conducted online, which allows researchers to access a large sample of a relevant population, such as homeowners or households, at risk of experiencing natural hazards. One-on-one interviews, which can be conducted over the phone or face-to-face, support researchers to gather greater detailed information from respondents than self-reported online surveys, as they provide the opportunity for interaction between researchers and participants. Based on the collected survey data, insights can be obtained regarding whether people over- or underestimate climate change-related risks and factors that influence risk perceptions. This can be relevant information for the design of communication policies that aim to improve risk awareness and enhance the implementation of adaptation measures (for example, Botzen *et al.*, 2015).

Surveys of demand for protection measures against climate change-related risks

Economic surveys regarding demand for protection measures against climate change-related risks, such as natural hazards, typically involve examining variables in demand for financial protection measures, including natural disaster insurance or physical measures that protect against the impacts of natural hazards such as flood-proofing measures or wind protection. Demand can be examined in a hypothetical market setting through surveying people regarding their willingness-to-pay for the measure or based on revealed preferences by enquiring whether people implemented the measure in practice. Moreover, individuals are often surveyed regarding a variety of variables that may influence this demand, such as their attitudes toward the measures, referred to as coping appraisals, including perceived costs, effectiveness and ability to adopt measures; risk perceptions; risk aversion and socio-economic characteristics. Analogous to studies regarding individual risk perceptions, surveys can be implemented online, or using one-on-one interviews. Based on the collected survey data, insights can be obtained regarding why some people have a high demand for measures to protect themselves against climate change risks while others do not, which can be relevant information for the design of policies that aim to improve the implementation of adaptation measures (for example, Poussin *et al.*, 2014).

Economic experiments

Economic experiments in the context of decision making under low-probability/high-impact risks typically involve exploring demand for risk reduction under various conditions. Typical enquires include individuals' willingness-to-pay for risk reduction measures, or whether they are willing to purchase an insurance or coinsurance policy with a specified risk, premium and deductible. The environment allows for manipulation control: the ability to change one variable of interest whilst maintaining other factors constant. In particular, these experiments also support the control for potential confounding factors which may influence risk reduction, and correlate with other variables of interest in tangible risk reduction decisions. Economic experiments differ in whether subjects' decisions are incentivized, the degree of artificiality of the choice environment and whether the experiment is conducted online with the general population (Robinson and Botzen, 2019a,b; Botzen and van den Bergh, 2012) or in a laboratory in the presence of an experimenter (Mol *et al.*, 2020). Incentivized economic experiments reflect actual market settings by providing monetary payments which increase/ decrease dependent on the outcome of the experiment, for example, by saving participants money if they invested in risk reduction measures after the occurrence of a randomly simulated flood. This technique may enhance the reliability of the choices made in the experiment compared with hypothetical, non-incentivized experiments. The experiments can be conducted online or in a laboratory, which usually implies smaller sample sizes but supports greater experimental control. Based on economic experiments, insights can be obtained regarding why some people have a high demand for measures to protect themselves against climate change risks while others do not, as well as the effectiveness of policies to improve the uptake of adaptation measures, such as financial incentives (for example, Mol *et al.*, 2018).

Assumptions

Survey studies assume that respondents answer questionnaires truthfully. This assumption also holds for non-incentivized economic experiments but can be mitigated to some extent in incentivized experiments in which participants get paid based on their choices and experimental outcomes.

Model verification

Estimates of hypothetical demand for protection measures can be compared with information regarding the level of implementation of these measures, if this data is available. The quality of the data collection approaches can be verified through checking if they follow guidelines of good practice, such as asking neutral questions, sampling large representative samples and incentivizing experiments.

Input data

The relevant input data are individual risk perceptions, which can be elicited with regards to probability, damage and natural hazard characteristics; individual risk reduction choices under various treatments/conditions in experiments, actual implementation of risk reduction measures or hypothetical demand for such measures in surveys; psychological factors applying a Likert scale response format; risk and time preferences and geographical factors retrieved from Geographical Information Systems (GIS). Other input data may include socio-economic factors such as income, wealth, age, education and gender, which can be used as control variables.

Outputs

Outputs can constitute information regarding the level of risk perceptions, demand for risk reduction measures, and factors which influence risk perceptions and demand for protection, including policies/ treatments to stimulate the implementation of protection measures.

These outputs can be used for evaluating policies that stimulate adaptation towards climate change-related risk. For instance, Mol *et al.* (2020) conducted an economic experiment to examine how individual investments in flood damage mitigation measures under increasing flood probabilities can be stimulated using financial incentives, such as insurance premium discounts and loans to support the initial investment costs. The results demonstrate that investments in flood damage mitigation increase with premium discounts, worry for the consequences of flooding and perceived efficacy of flood-proofing measures. These findings imply that individuals can be stimulated to implement adaptation measures through financial incentives from insurance and communication policies which focus on the potential consequences of natural disasters as well as the effectiveness of measures in limiting disaster damage.

Strengths and weaknesses

Strengths	Weaknesses
Surveys of perceptions towards climate change-related risks	
Online surveys support large sample sizes of the population of interest.	Survey data is often cross-sectional without experimental treatments, which does not allow for causal conclusions.
Combining survey and objective risk data supports the identification of misperceptions in natural hazard risks.	Risk perceptions are only one of several factors that influence climate adaptation.
Extensive information regarding survey questions are usually published, which supports ease of replication.	Some risk perception elicitation methods rely on numerical estimates, which requires controlling for numeracy skills.
Surveys of demand for protection measures against climate change-related risks	
Supports a greater direct examination of climate adaptation decisions than surveys exclusively on risk perception.	Survey data is often cross-sectional without experimental treatments, which does not allow for causal conclusions.
Online surveys support large sample sizes of the population of interest.	Elicitation of demand relies on hypothetical non-incentivized survey questions.
Extensive information regarding survey questions are usually published, which supports ease of replication.	
Economic experiments	
Experiments are a controlled setting that avoids confounding variables, meaning they can assess causal impacts on behaviour.	Some experimental control may be lost in online applications.
Incentivized experiments greater align risk reduction with tangible decisions.	Incentives are often small relative to climate change-related risks in practice.
Extensive information regarding the experimental method is usually published, which supports ease of replication.	Subjects are often not representative of the population of interest.

Suitability for rapid assessment

Depending on which journal the study is published, data may be accessible. Data is sometimes available from authors upon request. The application of methods also requires expert knowledge, for example, to design and analyse surveys and experiments. However, most results are easy to interpret.

Research gaps

Greater survey data regarding specific hazards and risk perceptions, as well as implemented adaptation measures, may be useful for testing risk communication in practice. More field economic experiment data on specific adaptation policies and risk reduction behaviour may be useful for testing specific policy interventions in practice, and/or the robustness of results found in the laboratory.

Given the cross-sectional data produced by survey research, it would be useful to conduct a greater number of surveys with the same population to examine risk perception and the implementation of adaptation measures over time, in particular, post disaster events. Further, given the high stakes of disaster risks, it is difficult to incentivize these in economic experiments. In this respect, future studies could examine to what extent the commonly applied incentive mechanisms bias behaviour.

Within an application setting, the studies reviewed have focused predominately on flood risk, and to a lesser extent, on other hazards such as wind and hailstorm. With a few exceptions (for example, Botzen *et al.*, 2015), survey studies have exclusively examined risk perceptions and greater research is required to examine risk misperceptions. Some adaptation policies have received insufficient testing in economic experiments, such as the amalgamation of disaster risks into one insurance policy, and nudges including setting insurance against disasters as a default option. Finally, studies predominately focus on risk perceptions and demand for adaptation measures by households, while greater research is required for companies and public sector decision makers.

3.5 Insurance

The models presented here estimate the impacts of climate change on the insurance sector and its clients. Moreover, they offer insights to guide decisions regarding reforms of financial compensation arrangements, such as insurance market structures; adaptation measures by insurers, their clients and the public sector and stimulating adaptation through insurance-related regulations and incentives.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.			

These models can be applied to assess various stages of adaptation policy and decision making:

- Step 2: Assessing risk and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options.

The models have been applied for simulating the impacts of climate change on natural disaster insurance by estimating effects on insured and uninsured losses, premiums, affordability of coverage, required reinsurance coverage or public funds and incentivized risk-reduction by policyholders. Moreover, they provide insights into desirable reforms of insurance products and insurance market structures, including public sector involvement in financing disaster risk in terms of determining optimal levels of deductibles and (primary and reinsurance) coverage levels, maintaining insurance affordability and providing incentives through insurance for implementing loss-reducing measures by policyholders. For instance, the models can provide insights into the impacts of climate change on the affordability of premiums of flood insurance and how much flood risk can be reduced through providing insurance policyholders financial incentives to adopt adaptation measures (for example, Hudson *et al.*, 2016).

Model and tool methodology

Statistical methods based on insurance claims (for example, Botzen and Bouwer, 2016) as well as catastrophe model approaches (Thistlethwaite *et al.*, 2018) have been commonly used to assess how insured losses may change as a results of climate change. These models are part of the risk assessment stage and may offer a starting point to examine whether adaptation measures are needed. Here, the focus is on models that explicitly link with adaptation in terms of reforms of insurance market structures and regulations or risk reduction measures, which can be divided in the categories of partial-equilibrium models, integrated catastrophe and insurance sector models, actuarial approaches and agent-based models.

Partial-equilibrium models

Partial equilibrium models simulate both the supply and demand side of the insurance sector from which information can be derived regarding premium and coverage levels and the market penetration in the market equilibrium. An example in the climate domain is the Dynamic Integrated Flood and Insurance (DIFI) model developed by Hudson, Botzen and Aerts (Hudson *et al.*, 2019), which simulates flood insurance markets in all EU member states. DIFI estimates riverine flood risk under scenarios of climate change and socio-economic development following a catastrophe model approach. This can provide input for an insurer supply module that estimates flood insurance premiums, and a consumer module that estimates unaffordability of flood insurance, demand for coverage and household investments in adaptation measures that limit flood risk. Flood insurance systems in countries are modelled according to different stylized versions of existing and potential reforms of market structures. The model simulates premiums, affordability of premiums, the market penetration and risk reduction that is incentivized through insurance by offering premium discounts for flood-proofing buildings. Based on a multi-criteria analysis (section 4.3) that encompasses criteria of equity and efficiency, the model evaluates whether it is desirable to reform flood insurance markets to cope with climate change.

Integrated catastrophe and insurance sector models

Most models in this domain are integrated catastrophe and insurance sector models which estimate how increasing risk from climate change affects an aspect of the insurance market without conducting a comprehensive assessment of both demand and supply. These models have examined the impacts of climate change on insured and uninsured losses and related aspects of insurance supply, such as premiums (Aerts and Botzen, 2011) and their affordability (Hudson, 2018), capital requirements (Jongman *et al.*, 2014), and government budgets for public insurance (Unterberger *et al.*, 2019). As a next step, the models are used for examining how insurance market reforms may limit these impacts, such as introducing public insurance (Hudson *et al.*, 2016). Moreover, they assess how adaptation measures, including flood protection and disaster resistant building practices, can limit these impacts. Some models account for how these adaptation measures can be stimulated through insurance regulations, such as building codes (Kunreuther, 2013) or financial incentives by means of premium discounts (Hudson *et al.*, 2016).

Actuarial approaches

Approaches from the actuarial discipline have been used for estimating risk distributions under climate change to derive impacts on premiums and desirable levels of insurance coverage to inform desirable reforms of natural disaster insurance markets. For instance, Paudel *et al.* (2015a,b) use actuarial approaches, including Bayesian Inference, to estimate probability distributions of flood risk as well as value at risk and tail value at risk statistics. The estimations are considered for the current climate and under scenarios of climate and socio-economic change. Based on this information, the model derives flood insurance premiums and optimal insurance and reinsurance coverage levels under private and public-private insurance systems.

Agent based models

Agent based models (see section 4.1 for more details) have been applied to estimate developments in natural disaster risk under climate change and how these depend on adaptation decisions by agents, which are influenced by insurance related incentives. These models are useful for simulating adaptation behaviour from multiple heterogeneous interacting agents, including households, governments and insurers whom react to each other's (adaptation) decisions. In particular, the models have been used for assessing the development of new structures in flood-prone areas (Jenkins *et al.*, 2017), flood-protection investments by governments and flood-proofing buildings by households (Haer *et al.*, 2017, 2019a,b), as well as how these decisions depend on insurance incentives, including premium discounts.

Assumptions

Key assumptions within all the insurance models relate to uncertainty in the risk estimates and risk reduction obtained from adaptation measures, as well as assumed cost loading factors in insurance pricing rules. Moreover, especially in the agent-based models, assumptions are made regarding the behaviour of agents, for which the empirical basis is often limited.

Model verification

Premium loading factors can be estimated using data on the costs of insurance provision. Risk reduction from adaptation measures can be based on empirical studies of damage savings of particular natural risk reduction measures. Behavioural rules can be calibrated using risk perception data or statistics regarding observed levels of insurance market penetration and implementation of risk reduction measures (Hudson *et al.*, 2019).

Input data

Natural disaster risk estimates under climate change scenarios are an important input in the insurance models. Often, these are local estimates of annual expected damage as estimated by catastrophe models that are forced with GCMs or RCMs (Jongman *et al.*, 2014).

Impacts of socio-economic developments on risk are estimated with 'shared socioeconomic pathways' (SSPs) scenarios (section 1.3.1) that influence income and growth in local exposed values to natural hazards (Riahi *et al.*, 2017). Some models require input data on the income distribution (for example, Hudson, 2018). Models which simulate insurance demand and risk reduction behaviour require data on risk perceptions or observed behaviour for calibration.

Outputs

These models produce estimates of developments in natural disaster risk, insurance premiums and their affordability, risk reduction from adaptation measures, insurance market penetration, financial reserves and capital requirements and insurance coverage levels.

These outputs can be used for evaluating the functioning of existing insurance arrangements for natural disaster losses and assessing whether reforms are required under expected climate change. For instance, the DIFI model has been applied to evaluate flood insurance market structures in all EU member states (Hudson *et al.*, 2019). Results highlight that the average flood insurance premiums may double in the EU up to the year 2050. This risk increase can be partially limited if insurance provides greater incentives to policyholders to adopt adaptation measures through risk-based premiums and premium discounts for implementing flood risk reduction measures. Moreover, the affordability of insurance can be improved by introducing reforms in most EU member states that involves a shift towards a public-private flood insurance system, which includes a public reinsurer, insurance coverage requirements and a limited degree of risk cross-subsidization.

Strengths and weaknesses

Strengths	Weaknesses
Partial-equilibrium models	
Examines the impacts of climate change on both supply and demand of natural insurance.	Requires input data for calibrating both insurer supply and consumer modules.
Insurance incentives can influence the adoption rate of adaptation measures.	Models focus on single hazards.
Outputs can be used for evaluating the desirability of reforms of insurance markets.	
Integrated catastrophe and insurance sector models	
Examines the impacts of climate change on supply aspects of natural disaster insurance.	Models require input data for calibrating supply modules, which involves restrictive assumptions.
Some account for the effect of insurance incentives on adaptation behaviour.	Do not give insights into insurance demand.
Outputs can be used for evaluating the desirability of reforms of insurance markets.	Models focus on single hazards.
Actuarial approaches	
Examines the impacts of climate change on supply aspects of natural disaster insurance, based on comprehensive risk distributions that represent uncertainty.	Reliably estimating the risk distributions is challenging with few empirical loss observations.
Outputs can be used for evaluating the desirability of reforms of insurance markets.	Does not provide insights regarding insurance demand and does not link with risk reduction.
	Models focus on single hazards.
Agent based models	
Provides insights regarding how insurance	Does not comprehensively model the

incentives influence adaptation decisions, while accounting for heterogeneous behaviour of other agents.	impacts of climate change on both insurance demand and supply and focus on single hazards.
	Small empirical basis for behavioural rules.

Suitability for rapid assessment

Most models have large data input requirements, and, for example, require input from catastrophe models that are often not open access. They also require expert knowledge and extensive studies for data inputs. As such, these models are not suitable for rapid analysis.

Research gaps

In many applications there is limited data available for calibrating insurance pricing rules as well as for consumer decisions with regards to insurance purchases and the adoption of risk reduction measures.

With a few exceptions (Hudson *et al.*, 2019), models often only focus on one aspect of the impacts of climate change on the insurance sector and adaptation, instead of offering a comprehensive integrated modelling framework of risk, insurance supply and demand and risk reduction behaviour.

The models reviewed in this category have been developed for water risk only and not for other relevant climate hazards, such as wind, drought and small-scale convective weather events such as hail. There are also only a few European scale applications (Jongman *et al.*, 2014; Hudson *et al.*, 2019; Haer *et al.*, 2019a,b).

Chapter 4.0: Other techniques

Under a range of different settings in which climate adaptation decisions are required, further analysis may be necessary to provide a holistic assessment that further inform impact assessments detailed in chapter 2. This chapter presents qualitative and semi-qualitative techniques of agent-based models, stakeholder and multi-criteria analyses where the interests of multiple stakeholders need to be considered.

4.1 Other non-standard modelling techniques: agent-based models and system dynamics

The agent-based models presented here simulate adaptation decisions by agents, such as households and governments, under climate change scenarios and estimate developments in adaptation processes as well as climate change related risks. They offer insights in order to guide decisions regarding adaptation measures by individuals, communities, farmers and the public sector.

Users and application

Model results can support decision-making of the following end-users:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).		x	x
Research	x	x	x
Civil society and NGOs.			

These models can be applied to assess various stages of adaptation policy and decision making:

- Stage 2: Assessing risk and vulnerability to climate change
- Stage 3: Identifying adaptation options
- Stage 4: Assessing adaptation options.

The models have been applied to the following climate change risks and adaptation processes:

- Flood and related cyclone/storm risk: individual flood-proofing measures, location decisions in flood zones, migration, real estate market responses, flood insurance reforms, flood risk communication, water storage, public flood protection and beach nourishment, spatial planning and flood zoning measures;
- Drought risk: irrigation by farmers, diversification strategies in agricultural production, grazing practices and migration.
- Health risk: water treatment technologies and social norms.

The models can provide insights regarding developments of risks and climate impacts on specific markets while accounting for adaptation decisions by various agents, developments in the implementation of adaptation measures, the effectiveness of adaptation strategies and interactions between decisions.

Model and tool methodology

Agent-Based Models (ABMs) have emerged as a method to model complex systems' behaviour at the micro-scale, which may inform emergent system-level outcomes including aggregated risk changes caused by climate change and how these may be reduced through adaptation strategies (Patt and Siebenhüner, 2005). ABMs examine the dynamic actions, reactions and intercommunications among a set of agents in a common environment in order to evaluate their performance and derive insights on their emerging behaviour and properties (Abar *et al.*, 2017). ABMs can account for heterogeneous autonomous agents whom react to other agents' decisions within social networks or base their decisions on learning and feedback, for example, from evolving climate change risks or government adaptation measures or policies such as risk communication campaigns. An attractive feature of ABMs is that they can account for collaboration and coordination of individuals and behaviour that deviates from economic rationality, for example prosocial behaviour, imitation and individual limited cognitive capabilities to process risks related to bounded rationality. Although some ABMs use ad hoc behavioural assumptions based on expert judgment, a good practice is to ground these rules in well-established microeconomic and psychological theories with parameter values from experimental or survey studies (for example, Haer *et al.*, 2017).

ABMs often contain either a catastrophe module component or a module that simulates changes in risks or market impacts from climate change over time, which is integrated with a further module that simulates dynamic responses by agents to these impacts over time. These models support the examination of developments in risks from climate change that account for adaptation decisions and assesses dynamic adaptation processes and their effectiveness. For instance, the agent-based model by Haer *et al.* (2019b) simulated how governments invested in flood-protection infrastructure with changing climate-induced flood risk over time for all river basins in the EU. Subsequently, the secondary impacts of how these flood-protection investments affected household decisions to locate in flood-prone areas and to flood-proof buildings was investigated. Another example, but on a smaller scale of three villages in Tanzania, is the RABMM-T model which assessed the impact of changes in rainfall due to climate change on household income, food production and, ultimately, resilience and human migration (Smith, 2014).

Assumptions

Key assumptions of agent-based models are those regarding the behaviour of agents for which the empirical basis is often limited.

Model verification

Some studies have calibrated the model inputs through collecting local survey data to represent agent characteristics and decision rules (Smith, 2014), validated model outcomes, such as predicted migration, with historical observations (Hassani-Mahmooei and Parris, 2012) or used scenarios to provide a range of outcomes between desired and realistic behaviour.

Input data

The design of agent-based models focusses on the decision rules of agents. To calibrate these decision rules, input data consisting of relevant socio-economic data that relates to household and demographic characteristics and social networks is required, such as income and risk perceptions, which may be available from government agencies or require collection through surveys.

Further important input data for ABMs include natural disaster risk estimates and/or their impacts on markets, such as agriculture or real estate, under climate change scenarios. Often these are estimated by catastrophe models (for example, Haer *et al.*, 2019b) or agricultural/crop productivity models (Hailegiorgis *et al.*, 2018) that are forced with GCMs or RCMs.

Outputs

These models produce estimates of developments in natural disaster and other climate change induced risks and market impacts, as well as developments in the adoption of adaptation measures. Consequently, these outputs can be used for evaluating the effectiveness of adaptation policies.

The agent-based model by Haer *et al.* (2019a,b) supports the examination of risk reduction derived from adaptation decisions by households and governments for all major river basins in the EU and for evaluating the effectiveness of insurance incentives to stimulate risk reduction by policyholders. The model results demonstrate that increasing flood risk by climate change can be offset significantly through effective adaptation decisions. In the short-term, adaptation at the household-level can provide greater risk reduction potential than governments. Moreover, investments in flood-protection by governments increases the potential flood damage over time given that they subsequently result in lower investments by households in flood damage mitigation measures and increased settlement within flood zones. Stimulating households to limit risk through insurance premium incentives can result in risk reductions of 38%.

Strengths and weaknesses

Strengths	Weaknesses
Provide insights into adaptation decisions by heterogeneous and interacting agents and how these limit climate impacts and risks.	Limited empirical basis for behavioural rules, which are often based on ad hoc assumptions and expert judgment.
Can evaluate the effectiveness of both hard (infrastructure) as well as soft adaptation strategies, such as risk communication.	Model validation is often complex.
Accounts for behaviour that deviates from rationality and prosocial behaviour in the context of decisions regarding adaptation.	Most ABMs do not comprehensively model equilibrium market outcomes in terms of demand and supply.
Can assess trends in disaster losses under climate change while accounting for dynamic processes of multiple agents.	

Suitability for rapid assessment

Most models have high data input requirements and, for example, require input from catastrophe models and survey data about behaviour that are often not open access.

Further, they require expert knowledge and extensive studies for data inputs, and therefore are not suitable for rapid assessment.

Research gaps

In many applications there is limited data available for calibrating the behavioural rules that determine the adaptation decisions in ABMs. Most ABMs also focus on a limited set of aspects of impacts of climate change, instead of offering a comprehensive integrated economic modelling framework to assess impacts on supply, demand and market outcomes. Additionally, the models reviewed have only been developed for water risk and not for other relevant climate hazards, such as wind and small-scale convective weather events such as hail. There are also only a few European scale applications (Haer *et al.*, 2019a,b), and as such require greater application at higher geographical scales.

4.2 Qualitative assessments: stakeholder analysis

Stakeholder analysis aims to generate knowledge on individuals and organisations in order to understand their behaviour, intentions, inter-relations and interests and determine their relevance to a project or policy.

Users and application

End users include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

Stakeholder analysis is a prerequisite to ensure the participation of relevant stakeholders in developing and implementing effective adaptation policies. While it is key to undertake stakeholder analysis in the early stage of policy formulation, stakeholder analysis can support all steps of the adaptation policy cycle:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options
- Step 5: Implementation
- Step 6: Monitoring and evaluation

Stakeholders' roles and contributions could vary according to the policy stage. Stakeholder analysis can support understanding regarding how an individual or organisation can be affected by and can affect a decision, as well as which individual(s) or organisation(s) can contribute towards developing potential solutions, thus supporting decision making or the implementation of selected options.

Model and tool methodology

Stakeholder analysis includes two main steps: i) identifying and categorizing stakeholders; ii) identifying the relationship among them. A number of methods can be used for each of these activities.

Stakeholder identification and categorization methods

Common methods for identifying stakeholders include snowballing sampling, semi-structured interviews, focus groups and a combination of these methods. Stakeholders can also be identified through census data, document analysis and self-selection (Chevalier and Buckles, 2008). As the identification is usually conducted in a top-down manner by the analysts/researchers and may thus reflect their interests and bias, the process should be designed using an iterative method and include, for instance, scoping studies and follow up meetings.

Stakeholder categorization can be both top-down (analytical categorisation) and bottom-up (reconstructing methods) (Reed *et al.*, 2009). Analytical categorization is conducted by the researcher/analyst based on some theoretical assumptions on how the system works. Stakeholders are assigned to specific typologies based, for instance on whether they have power, legitimacy or urgency (Mitchell and Wood, 1997). Matrices are commonly used to conduct these analysis (Van Der Heijden, 1996). An example is the 'alignment, interest and influence matrix' which supports understanding regarding how the main policy audience of an intervention stand in relation to its objectives and influencing approaches (Mendizabal, 2007).

Methods investigating stakeholder relationships

Social Network Analysis (SNA) is used to identify and analyse relationships defined by links of socio-institutional relationships among nodes, constituting individuals, organisations or interest groups (Wasserman and Faust, 1994). SNA can be both quantitative and qualitative. Quantitative SNA provides measures and indicators to describe the structure of the system and the roles of nodes within it. Qualitative SNA encourages participation across different viewpoints and actors (Bharwani *et al.*, 2013). Knowledge mapping is usually employed with SNA to identify stakeholders who would work effectively in synergy and power relations among them (Reed *et al.*, 2009).

Input data

Data for stakeholder analysis can be obtained using human involvement through focus groups or semi-structured interviews, or without human involvement such as using documents or census data. When involving human participants, ethical challenges should be considered with respect to consent, confidentiality and anonymity and risk of harm.

Outputs

Stakeholder analysis generates knowledge regarding individuals and organisations, including characteristics, behaviour, intentions, inter-relations and interests. This supports the identification of individuals or organisations that should be involved in a participatory process. Greater in-depth information on stakeholders' relationships can be obtained by analysing institutional arrangements and settings.

Stakeholder analysis is important for strategic adaptation planning at different levels (Wamsler, 2017). Risk-based decisions, such as flood protection measures, require stakeholder engagement at the preliminary phase of any intended climate risk management plan or strategy in order to select the optimal course of action under uncertain situations. Further, participatory and accountable decision-making processes improve the effectiveness of possible interventions.

Calliari *et al.* (2019) employed stakeholder analysis to map the landscape of organizations involved in adaptation and disaster risk reduction activities in coastal Tabasco, Mexico. Governmental entities were identified through an extensive review of national and local legislative and planning instruments supporting adaptation, disaster risk reduction and natural resource management. Knowledge-generating institutions and civil society organisations were identified through online searches and interviews with local experts. Civil society organisations were identified through snowballing techniques. The level of collaboration among organisations were subsequently assessed through a quantitative SNA. Other studies employing SNA to identify key actors in adaptation decision making include Bowen *et al.* (2014) and Varela-Ortega *et al.* (2016).

Strengths and weaknesses

Strengths	Weaknesses
▪ Identify potential stakeholders, their interests and areas of concern to address. ▪ Supports greater outreach to key stakeholders. ▪ Prioritizes stakeholders for inclusion. ▪ Enhance the legitimacy of adaptation activities through incorporating stakeholders' views. ▪ When conducted in a participatory manner, stakeholder analysis can promote ownership and uptake of adaptation activities. ▪ Stakeholders can be visualized in an effective manner. ▪ Stakeholder analysis can provide mechanisms to positively influence other stakeholders. ▪ Network building: stakeholders engage and learn from each other.	▪ If the timeframe of prospective analysis is extensive or the results are not applied within a short time period, the relevance of the analysis could reduce. ▪ Selection bias and marginalization of certain group(s) could occur. ▪ Stakeholders may have limited time and financial resources for engagement with participatory analysis. ▪ Increasing costs due to increasingly sophisticated tools that are context-specific and address a wide range of climate risks. ▪ A skilled facilitator may be required. ▪ A combination of methods may be required in order to be effective, for example, snowball mapping and semi-structured interviews. ▪ It is a time-consuming process.

Suitability for rapid assessment

Methods for stakeholder identification can be time consuming, for example, through interviews and focus group, and require continued iterations. It is also important to allocate appropriate time to the analysis to ensure key actors are not excluded.

Research gaps

Stakeholder analysis is well-established in policy analysis, especially in the management, development and health fields (Brugha and Varvasovszky, 2000).

4.3 Semi-quantitative assessments: multi criteria analysis (MCA)

Multi Criteria Analysis (MCA) is a non-monetary assessment to rank different options using a wide range of criteria that can account for both quantitative and qualitative data. These criteria can also be weighted to reflect their relative importance.

Users and application

The end users of these methodology include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

MCA can be most useful for the policy cycle at:

- Step 4: Assessing adaptation options

MCA is a tool for prioritizing measures and support decision makers to evaluate their adaptation options under a wide range of criteria. Outputs from an MCA are either a single most preferred option, ranking of measures that can help prioritizing actions, a short list of options for further evaluation or characterization of acceptable or unacceptable possibilities (UNFCCC, nd).

Model and tool methodology

MCA provides a systematic approach for ranking adaptation options against a range of decision criteria. The criteria can be evaluated in a quantitative and/or qualitative manner, either using physical, monetary or non-monetary units. Additionally, they can be weighted or ordered to reflect the relative importance of different criteria under different circumstances. Different MCA methods, predominately based on their aggregation methods and supporting tools, are available which can address various problems arising from impact assessments or evaluations. Some examples of common approaches are (based on Dodgson *et al.*, 2009):

Method	Description
Linear additive models	Most MCA approaches use this model. It shows how an option's values over multiple criteria can be combined into one overall value. This is done by multiplying the value score on each criterion by the weight of that criterion, and then adding all weighted scores together. Pre-condition: criteria must be mutually preference independent. This is applicable when uncertainty is not incorporated into the MCA model.
Multi-attribute utility theory	This is a normative model for decision making that accounts for uncertainty risk within its mathematical model. It also evaluates several criteria and incorporates this within the

	decision support model. This option does not necessarily assume that the options are preferentially independent.
The analytical hierarchy process	Also develops a linear additive model, however the weights of the different criteria and performance scores for the different alternatives are based on pairwise comparisons. This means that this method addresses: 'How important is criterion A relative to criterion B?'
Multi-criteria decision analysis	A form of MCA (both an approach and a set of techniques) which provides a ranking of options from the most to least preferred. The options may differ in the extent to which they achieve several objectives and no single option is obviously optimal for achieving all objectives. A trade-off is usually evident amongst the objectives: for example, options that are more beneficial are also usually more costly. It is ideal to assess and disaggregate complex problems that are characterized by any mixture of monetary and non-monetary objectives.
Outranking methods	Outranking seeks to eliminate alternatives that are 'dominated'. One option outranks another if it outperforms the other on enough criteria of sufficient importance, as reflected by the sum of the criteria weights. It indirectly captures some of the political realities of decision making and can be useful to explore how preferences between options can be derived.
Qualitative data inputs	The key characteristic is that the information within the performance matrix or application of preference weights consists of qualitative judgements. One method approximates the linear additive model which requires extra assumptions for greater output precision. An alternative uses an outranking method especially designed for qualitative valuations. The performance of options and the weight of criteria are qualitatively evaluated through classifying them into categories.
Fuzzy sets	Attempt to capture the impreciseness of language, for example, 'fairly attractive' or 'rather expensive'. These methods tend to be challenging due to their complex theoretical underpinning. Fuzzy arithmetic attempts to capture these qualified assessments using a membership function through which an option would belong to the set of, for example, 'attractive' options with a given degree of membership between 0 and 1.

Some example tools include: NAIADE from the Joint Research Centre (JRC) (Russi & Tabara, n.d.), Promethee & GAIA[64] ("PROMETHEE", 2011), MacBeth (software, excel), Risk-KIT Multi-Criteria Analysis Tool (MCA) which assess alternative Disaster Risk

[64] Preference Ranking Organization Method for Enrichment of Evaluations & geometrical analysis for interactive aid

Reduction measures with stakeholders ("RISC-KIT", n.d.), Decision deck and Excel tools such as the MCA tool from the Dutch Routeplanner project within the ECONADAPT toolbox (ECONADAPT, n.d.). This last example was used to "*provide a 'systematic assessment' of potential adaptation options to respond to climate change in the Netherlands in connection to spatial planning*" (Van Ierland et al, 2007).

MCA should be applied when a single criteria approach, such as Cost Benefit Analysis (section 5.1), is not suitable, where significant environmental and social impacts cannot be assigned monetary values or are difficult to quantify via secondary data and expert judgement is required. It is also a useful methodology when engagement and consensus of stakeholders is required.

Assumptions

The main assumptions in this method constitute the weighting and scoring of criteria for adaptation options, which are based on expert judgement. This presents two issues: first, it assumes that their expertise is sufficient. Second, individuals with appropriate expertise may also have a conflict of interest in the decision outcome, (Dodgson *et al.*, 2009) promoting judgement biases from invested stakeholders.

Model verification

As a final step, a sensitivity analysis can be conducted to examine how the results, such as the ranking of options, might change under different scoring or weighting systems. This can demonstrate the robustness of measures under different weightings (Dodgson *et al.*, 2009).

Input data

The data requirements for an MCA are the metrics for each criteria evaluation, however the key characteristic is that the information within the performance matrix or application of preference weights consists of qualitative judgements. Some common criteria include costs of the measures; co-benefits in monetary or non-monetary terms; effectiveness of the measure such as the expected capacity to achieve a target; feasibility; acceptance, technological, regulatory or social readiness and robustness.

Moreover, when applying MCA to climate adaptation strategies, it is necessary to include climate model information/projections, which are required to provide indications of future climate change impacts, for example, in terms of changes in temperature, weather extremes, runoff and sea level rise. This provides potential future climate conditions under which the performance and effectiveness of adaptation strategies can be tested (Rastall, 2018).

Outputs

The main outputs of this method can be a single most preferred option, ranking of measures that can support action prioritisation, a short list of options for further evaluation or characterization of acceptable or unacceptable possibilities (UNFCCC, n.d.).

In the Netherlands, MCA was used for a national level early programmatic analysis of adaptation as part of a national strategy development. Adaptation options were identified in workshops for different sectors, such as agriculture, nature, water, energy and transport, housing and infrastructure, health and recreation and tourism. Common criteria were identified and weighted: importance, urgency, no regret, co-benefits and effect on climate mitigation. The final output of this project was a relative ranking of adaptation options based on a weighted sum of criteria, highlighting that in the Netherlands, integrated nature and water management and risk-based policies are highly ranked, followed by policies to achieve 'climate proof' housing and infrastructure. As part of this process, an inventory of adaptation options were developed for each sector, as well as a qualitative assessment of the long-term effects of each adaptation options for the Netherlands and a database which supported the ranking of various options according to a set of criteria (De Bruin *et al.*, 2009).

A second case study applied an MCA for flood protection of the Kokemäki river in Pori, Finland. The analysis produced a robust ranking of the considered flood protection alternatives. The workshop participants preferred a high level of protection against floods, either employing embankments or dredging. The results demonstrate that stakeholders are concerned with the risk of flooding and would prefer to pay for protection to reduce the risk level (Porthin *et al.*, 2013).

Strengths and weaknesses

Strengths	Weaknesses
▪ MCA can include different environmental and social indicators. ▪ Can combine qualitative and quantitative data, monetary and non-monetary objectives. This enables the consideration of a wider range of criteria, especially in instances when quantification is challenging or limited. ▪ Relatively simple and transparent method which can be conducted at a relatively low cost. ▪ Supports stakeholder engagement and can be based on local knowledge or expert judgement.	▪ MCA cannot demonstrate that an action provides greater welfare than it detracts, unlike Cost-Benefit Analysis. ▪ The 'best' option can be inconsistent with improving welfare (Dodgson *et al.*, 2009). ▪ When assessments incorporate a 'business as usual' scenario, the benefits of not spending money may promote it as an optimal solution over the longer-term benefits of adopting adaptation measures. ▪ Results require further interpretation. ▪ Can be subjective as different expert opinions may provide different criteria scores or weightings. ▪ Stakeholders may have a lack of knowledge and key options may not be incorporated – only proposed options are assessed.

	▪ Analysis of uncertainty can often be highly qualitative.

Suitability for rapid assessment

MCAs can apply methods with different levels of complexity depending, among other factors, on the aggregation method and on the number of criteria to analyse. A simple MCA for a rapid assessment should consider a limited number of adaptation options and criteria to analyse. The larger the number of variables, the greater the data requirements. Moreover, the organisation and conduction stakeholder involvement can be time consuming yet, in the majority of cases, is recommended.

Research gaps

MCAs are widely applied however the application of fuzzy sets could be expanded. Fuzzy sets are challenging to apply due to the complexity of operationalizing or capturing imprecise calcifications yet developing their use may be beneficial in fields such as climate change where the level of uncertainty and difference of opinions can significantly differ (Dodgson *et al.*, 2009).

Chapter 5.0: How to use the information (principals and methods)

This chapter presents methods which can use information from the previous four chapters to support decision making based on different requirements and situations, for example, when decision makers are operating under high degrees of future uncertainty or comparing the effectiveness of different identified adaptation strategies.

5.1 Cost – benefit analysis

Cost-Benefit Analysis (CBA) is a framework which supports transparent, coherent and systematic decision-making based upon a common monetised yardstick that can be used to evaluate various risk reduction strategies (Czajkowski *et al.*, 2012; Mechler and Islam, 2013). CBAs are widely applied on all geospatial levels to assess the economic feasibility of adaptation measures.

Users and application

The main users are:

	European	**National**	**Local/Project**
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).		x	x
Research	x	x	x
Civil society and NGOs.			

Cost-benefit analyses are primarily used in:

- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

CBAs are primarily applied as a decision-support tool to help prioritise adaptation measures. The output of these models highlights the benefits of adaptation measures and helps to rank adaptation options in terms of their monetary value.

Model and tool methodology

The standard economic literature distinguishes between three types of CBAs: (i) Financial, (ii) Economic and (iii) Social. Financial CBAs (FCBAs) consider financial revenues and costs. This is unsuitable to justify public expenditures on Disaster Risk Management (DRM) since most benefits are not in the form of financial revenues. Applied to the decisions of households to invest in DRM measures, FCBAs compare the costs of measures with the reductions in expected financial damages.

Economic CBAs (ECBAs) consider projects from the perspective of societies. Costs and benefits are valued in terms of willingness-to-pay or willingness-to accept how much consumption society is willing to exchange for the inputs and outputs of the projects. ECBAs focus on individual wellbeing, measured through utility and incorporate indirect and intangible costs and benefits.

Social CBAs (SCBAs) are different from ECBAs since wellbeing gains and losses for different groups or individuals are weighted, as specified by the social welfare function, to derive an aggregate social welfare value.

In a CBA, all costs and benefits accrued over time are monetized and aggregated to support comparison using a common economic efficiency criterion. In general, if the stream of discounted benefits exceeds the discounted costs, positive net present value economic benefits, a proposal is considered desirable and economically efficient. When comparing options, including not acting, the option with the highest net present value is considered optimal. In this way, CBA is similar to rate-of-return assessment methods undertaken by firms to assess whether or not an investment is profitable. However, unlike private investment decisions, CBA is often used to estimate the overall profit/ benefit to society, and thus whether or not social welfare is maximized in regard to the policy. One of CBA's main strengths is its explicit and rigorous accounting of benefits and costs within a common metric of monetary value (Mechler *et al.*, 2014).

Assumptions

When assessing the cost and benefits of climate adaptation measures, an essential assumption is the choice of discount rate to determine the net present value. Specifically, deciding to choose a 2% discount rate over a 4% discount rate may determine whether an adaptation option is feasible or not. Secondly, there is often limited information available regarding all the costs and benefits within the analysis. This requires the analyst to make assumptions, for instance, regarding the exact cost of the adaptation measure. Thirdly, as the benefits of an adaptation measure are defined as the resulting risk avoided, a plethora of assumptions are often incorporated in risk analysis, such as the reconstruction cost and the relation between the hazard intensity and the damage.

Model verification

Most CBAs are performed ex-ante in the assessment of possible adaptation options for a given area or asset. CBA can, however, also be performed ex-post to evaluate implemented risk reduction measures. However, this is not common practice. Yet, when conducted on a large scale, ex-post evaluations can provide a method to validate the assumptions and approaches.

Input data

The climate data required depends on the type of adaptation measures under review. As the benefits of adaptation are often expressed in terms of avoided risk, hazard footprints are required for a set of return periods, for example, a flood map with a return period of 1/50 for Europe, to estimate the risk. Hazard footprints are often freely available, such as the GloFAS[65] data for flooding (Van Der Knijff *et al.*, 2010), and WISC[66] for extratropical storms (Maisey *et al.*, 2017).

Socio-economic data on GDP growth and discount rates specific to adaptation measure location are required, which can be obtained from Eurostat. Other information regarding the cost of the adaptation measures are required, such as the initial cost of implementation and the yearly maintenance cost. This is often based on expert interviews and stakeholder workshops.

[65] https://data.jrc.ec.europa.eu/collection/id-0054

[66] https://wisc.climate.copernicus.eu/wisc/#/

Outputs

Outputs of CBAs include the benefits and cost of adaptation measures and the benefit-cost ratio (BCR). When assessing the cost and benefits of a suite of adaptation measures, CBA can be used to rank the outputs under different assumptions to identify the optimal, economically efficient adaptation measure.

Strengths and weaknesses

Strengths	Weaknesses
▪ Rigorous framework based on comparing costs with benefits. ▪ Straightforward and widely understood tool for decision-making to support understanding regarding the feasibility of adaptation measures.	▪ Net present value is sensitive to the choice of the discount rate. It can, however, prove to be challenging to determine the correct discount rate. ▪ All elements included within the analysis need to be monetised. It can therefore be challenging to incorporate non-monetary aspects, such as social vulnerability and ecosystem services, within a CBA.

Suitability for rapid assessment

Rapid access to input data varies given that CBA for adaptation is dependent on a range of data inputs. To estimate the benefits, information regarding the avoided risk is also required. If this is not available, then it should be calculated first. Information on discount rates can be quickly accessible. The cost of adaptation measures is often not readily available.

The general framework of a CBA is straightforward and easy to apply. If high quality and complete data are available, a CBA can be rapidly conducted. However, it is essential that all elements are included in the CBA. When elements are missing, it may result in suboptimal decisions.

Research gaps

While the analysis itself is straightforward and unambiguous, the choice of the discount rate and which elements to include as costs or benefits are not. As such, more research is still required on the “right” choice of the discount rate.

Moreover, a CBA may provide suboptimal outcomes (resulting in suboptimal decisions) when elements are missing for either costs or benefits. Not including all the elements in the analysis is often the result of either not knowing what to include or because crucial information is missing due to a lack of data or information. How to deal with the uncertainties in the outcome as a result of this of data and information gap is often still ignored and should be included in the analysis more consistently. This is primarily an issue for assessing the costs of implementation for adaptation. Academics are often not aware of the costs of implementation, which results in making crude assumptions. To solve this, more work should be conducted to estimate the cost of adaptation measures.

Finally, the cost information of adaptation measures are often based on strong assumptions made by the modeller or analyst.

5.2 Cost effectiveness

Cost-Effectiveness Analysis (CEA) can be used to compare and rank the relative attractiveness of options and to identify the least cost combination to achieve pre-defined targets using cost curves.

Users and application

End users of these methods include:

	European	National	Local/project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

Cost effectiveness can be applied to the policy cycle:

- Step 4: Assessing adaptation options

This method can support decision support to help prioritise adaptation options by producing cost-curves of ranked options and information on achieving targets most efficiently.

Model and tool methodology

Cost-Effectiveness Analysis (CEA) is a widely used decision support tool. It compares alternative options for achieving similar outputs or objectives. In this regard, it is a relative measure providing comparative information between choices. It has been widely used in environmental policy analysis because it quantifies benefits in physical terms. It has also been the primary decision support tool used for mitigation, where it has particularly strengths due to the focus on technical optimisation for a simple relative metric such as GHG emission reductions. At the technical or project level, CEA can be used to compare and rank alternative options. It achieves this through assessing options in relation to the cost per unit of benefit delivered, such as the cost per tonne of pollution abated. This identifies options that can deliver the highest benefit for lowest cost, the most cost-effective, as well as ranking different options.

Such an analysis can be used for benchmarking, requiring a suitable relative adaptation metric to assess the benefits against. For adaptation, this varies widely unlike for mitigation which uses a single metric for all sectors. At the project, policy or programme level, where combinations of options are required, CEA can be used to assess the most cost-effective order of options and therefore identify the least-cost path for achieving pre-defined policy targets. This is undertaken through the use of marginal abatement cost (MAC) curves. The approach can also identify the greatest benefits possible with the available resources, as well as to support establishing targets by selecting the point where cost-effectiveness significantly reduces where there are disproportionately high costs for low benefits.

As CEA is a decision support tool, it can be applied to existing model outputs, although some models also include the relevant parameters to undertake CEA within the modelling framework. A variation of the approach uses cost-benefit analysis to derive ranking of options, but presents these as a cost curve (ECA, 2009).

CEA is considered most useful for near-term adaptation assessment, particularly for identifying low and no regret options. The approach can be applied to both market and non-market sectors, but it is particularly relevant for areas that are difficult to value in monetary terms, for example, for biodiversity and health (fatalities). The use for long-term assessment is considered most appropriate when used as part of an iterative adaptive management analysis, rather than as a tool on its own. It is most applicable and relevant where there is a clear headline indicator and a dominant impact and is less applicable for cross sectoral and complex risks given that it generates a single metric. It is thus more applicable when there is already agreement on sectoral objectives and effectiveness criteria. It is more appropriate where climate uncertainty is low and good data exists for cost/benefit components.

Assumptions

The key assumptions include the metrics used and the ability to assess the level of adaptation benefit in quantitative terms. Importantly, CEA uses a techno-economic framing, focusing around least cost optimisation. This does not align to the core concepts of adaptation as a process, and the need for capacity building as well as delivering adaptation. The method tends to overemphasise technical measures, for which it is easier to assess the benefits. Another key assumption regards uncertainty. CEA tends to be presented as single values and central cost curves, thus omitting consideration of uncertainty. It is possible to address this by sampling across multiple scenarios/model outputs, but this has resource implications. The final assumption is that CEA optimises to one metric. It is therefore not suited to adaptation applications where there are multiple criteria involved. This limits the application in mainstreaming cases, as well as in many decisions where multiple metrics are important.

Model verification

This varies with sector and whether a model has been used. Information on relevant metrics can be found in the sector impact models.

Input data

Full cost data is required, capital and operating costs, expressed in equivalent economic terms, as well as data on unit effectiveness. For policy applications, additional information is required in the form of baseline risks and the total potential for each option. The climate and socio-economic data requirements depend on the sector and application, with the key issue constituting the choice of metric. A summary of sector metrics includes (Watkiss and Hunt, 2012):

Sector	Possible metric
Health	Cost per Disability-Adjusted Life Year (DALY), cost per fatality or cost per life year saved (impact metrics). Health thresholds include maximum occupational temperatures and

	comfort levels.
Sea level rise/ floods	Cost per reduction in land area at risk or number of people at risk (exposure metric) or expected annual damages (economic metric). Cost per hectare. For the measure relative to value of land protected per hectare (impact metric). Pre-defined acceptable risks of flooding as objective / threshold level for adaptation.
Agriculture	Impact based metrics include cost per unit of crop yield, production or land value, however this depends on risk as could, for example, be a reduction in water stress. Possible headline indicator is cost per change in value added as a result of adaptation measures.
Water resources	Impact metrics for water availability (household) and cost per m^3 of water provided. Possible thresholds in terms of environmental quality (directives) or acceptable flows. Possible thresholds for risk of supply disruption.
Ecosystems and biodiversity	Critical targets (sustainable levels) and standards (overall objective). Possible cost per unit of ecosystem services.
Business and industry	Possible headline indicator is cost per change in value added as a result of adaptation measures. Could also include acceptable risk levels for infrastructure or service supply.

Outputs

Outputs of this tool include analysis of the cost-effectiveness as cost per unit of adaptation benefits achieved, cost-effectiveness ranking of different options and cost-curves of least cost combination of options.

Cost-effectiveness is already applied in many sectors that are relevant to adaptation, such as health and flooding, and therefore has the potential for appraising options to address future climate change. In the adaptation domain, CEA has also been used in risk-based flood protection assessment, for example, for assessing the cost-effectiveness of achieving flood protection targets, defined as a level of acceptable risk such as protection against a 1 in 100-year return period. This has been used in global, European, national and local studies.

The development of flood protection cost-curves, examining the reduction in flooding from different options. Examples include applications which explore water supply and demand options. Boyd *et al.* (2006) estimated adaptation costs for anticipated water deficits up to 2100, using indicative cost-yield curves and cost-effectiveness analysis for water regions in the UK. The Adaptation Sub Committee (ASC, 2011) also developed household water and heat adaptation cost curves for the UK. There have been applications in the health sector examining the cost per DALY for water and sanitation measures.

Strengths and weaknesses

Strengths	Weaknesses
▪ Benefits are expressed in physical terms and therefore does not require monetary valuation of benefits. Increases applicability to non-market sectors. ▪ Relatively simple approach to apply and provides easily understandable ranking and outputs that easy to understand. ▪ Frequently used for mitigation, and thus the approach is widely recognised and has resonance with policy makers. ▪ Use of cost curves can assess different policy targets and how to achieve these for the lowest cost, examine how to achieve greatest benefits for available resources, or explore the cost implications of progressively greater ambitious policies.	▪ Optimises to a single metric, which can be difficult to determine. Less applicable for cross-sectoral or complex risks. ▪ The focus on a single metric omits important risks and does not capture all costs and benefits (attributes) for option appraisal. ▪ Tends to work best with technical options and can therefore omit or assign lower priority to capacity building and soft (non-technical) measures. The sequential nature of cost curves ignores portfolios of options and inter-linkages. ▪ Does not lend itself to the consideration of uncertainty and adaptive management, tending to work with central tendency.

Suitability for rapid assessment

Cost effectiveness has some potential for rapid assessment as a method for undertaking a relatively quick ranking of options, for example, with indicative data on costs and effectiveness. This is particularly relevant in some sectors where relatively comparable metrics are used, such as for water, or where valuation is challenging such as health and ecosystems.

Research gaps

Research gaps include a need to develop cost-effective metrics for many sectors, for example, for ecosystems and biodiversity, where the non-monetary approach has a higher application. There is also a need to research how to consider cost-effectiveness, which prioritises one metric against other criteria, especially to use it in mainstreaming applications or in more applied cases. Other research priorities include better information on costs and the transferability of these costs between locations, with similar issues regarding the effectiveness of adaptation and transferability. Finally, the approach tends to be linear and technology focused. A research priority is to investigate how to include uncertainty and adaptive management approaches in CEA and broaden its scope to consider non-technical options.

5.3 Decision support systems (DSS)

Decision Support Systems (DSSs) are computer-based software aimed at assisting planners and policy makers across different phases of the adaptation policy and decision-making processes. They have been developed in recent years to support climate change impact and adaptation assessments by integrating simulation models operating at different scales of climate, ecological and economic models, and by applying increasingly sophisticated methodological approaches and user-friendly interfaces (Ramieri *et al.*, 2011).

Users and application

End users include:

	European	National	Local/project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.	x	x	x

DSSs can be applied to support the implementation of different phases of the adaptation policy and decision making as follows:

- Step 1: Preparing the ground for adaptation
- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options
- Step 6: Monitoring and evaluation.

DSS may help to (i) integrate heterogeneous information, for example, spatial vector and raster data model outputs; (ii) provide answers to different management questions, such as what is the risk level and what are the greatest affected targets?; (iii) choose among alternative management measures of prevention and adaptation. They can assist planners and policy makers across different phases of the decision-making process, supporting rather than replacing their judgment and, at length, improving effectiveness over efficiency (Janssen, 1992).

DSSs produces accurate, relevant and complete timely information, such as quantitative results from model projections and forecasts, historical data analysis and display of trend analysis and performance monitoring, recommendations, retrieving relevant documents, sharing of content and interaction with end-users.

Model and tool methodology

In the environmental resource management sector, DSS are generally classified into two main categories: Spatial Decision Support Systems (SDSS) and Environmental Decision Supports Systems (EDSS).

SDSSs are designed to help decision-makers with complex spatial problems (Densham, 1991) and usually integrate a GIS technology computer system capable of assembling, storing, manipulating and displaying geographically referenced information. They are equipped with interactive communication capabilities between the GIS components and the peripheral software tools (Sharma, 2012).

Environmental Decision Supports Systems (EDSS) integrate relevant environmental models including climate change and impact models, databases and other assessment tools, usually coupled within a Graphic User Interface (GUI) and GIS functionalities (Fabbri, 1998; Poch *et al.*, 2004; Uran and Janssen, 2003).

DSSs addressing climate change are the result of the combination of SDSS and EDSS, and are specifically used to support decision makers in the sustainable management of natural resources and in the definition of possible adaptation and mitigation measures (Torresan *et al.*, 2010). A key representation of these systems is GIS supporting the capture, manipulation, process, analysis and display of spatial data (Nobre *et al.*, 2010). The main structure of DSSs includes three key components: i) a database management system, which supports the organization of basic spatial and thematic data which facilitates their efficient processing; ii) a model management system, including several quantitative and qualitative models supporting data analysis; and iii) powerful, but simple and user-friendly interface design, supporting communication with the system and visualization of outcomes.

Some examples of DSSs developed to provide support across climate change risk assessments and management are the WADBOS DSS; the CVAT (Community Vulnerability Assessment Tool); KRIM DSS; DITTY; the DIVA DSS (Dynamic and Interactive Vulnerability Assessment); SimCLIM (Simulator model System for Climate Change Impacts and Adaptation); the Tyndall Coastal Simulator; the DSS DESYCO (DEcision support SYstem for COastal climate change impact assessment); THESEUS DSS; FREEWAT and GOWARE-DST (Guide towards Optimal WAter Regime).

Assumptions

The conceptual frameworks and methodological assumptions underlying the different DSSs include, for example, use of qualitative data, application of scores and weights for data aggregation and integration of expert judgments, which may be considered too simplistic for the end-users to trust the reliability of the results. However, this limitation can be overcome by running a sensitivity analysis of several configurations of scenarios, scores and weights for the same case study.

The implementation of the overall analytical chain underpinning climate change impact assessments may require significant quantities of multi-faceted data, including climate, socio-economic, environmental and physical data.

Model verification

Resulting output from the application of DSSs across different spatial and temporal scales and geographical locations can be validated using records of historical data in a reference scenario. Alternatively, DSS results can be validating through comparison of analogous study results, performed using different methods, models or tools analysing the same timeframe and/or location.

Input data

Working in an integrative way, DSSs provide tested methodologies for supporting complex environmental decisions by providing a systematic, quantitative and transparent way of evaluating and integrating monitoring data, numerical model projections, socio-economic considerations, experts' judgment and stakeholder needs and perspectives.

Outputs

DSS outputs include GIS-based maps, including hazard, exposure, susceptibility, risk and damage maps; and indicators calculated at the end of the assessment and report summarizing key results and recommendations for adaptation planning as well as the DSS configuration parameters.

By integrating heterogeneous data, including socio-economic, hydrological, environmental and ecological information, DSSs can be widely applied within climate adaptation and environmental management contexts. For example, the DSS DESYCO was applied to low-lying coastal plains and islands in the North Adriatic coast, the Gulf of Gabes and the Republic of Mauritius to evaluate sea level rise inundation, storm surge flooding and coastal erosion risks (Gallina *et al.*, 2019; Rizzi *et al.*, 2016; Jonathan Rizzi *et al.*, 2015; Torresan *et al.*, 2017); river basins and groundwater systems within the Upper Plain of Veneto and Friuli-Venezia Giulia and the Marche Region to assess changes in groundwater availability and quality (Baruffi *et al.*, 2012; Pasini *et al.*, 2012); and in the North Adriatic Sea to analyse water quality variation (Rizzi *et al.*, 2015). Resulting outputs from these applications supports the evaluation of the impacts produced by interactive stressors on multiple elements at risk. This supports public authorities to prioritize vulnerable areas at the regional scale from impacts through development and implementation of suitable climate adaptation strategies.

Another relevant DSS for land-use and water management is the GOWARE-DST, developed in the frame of the PROLINE-CE projects to support end users in selecting, prioritizing and promoting the most suitable Best Management Practices. Specifically, the DSS accounted for the users' criteria of water protection functionality, cost and time of the implementation, multi-functionality and robustness, to protect drinking water resources from the impacts of flood and drought events. It relies on operative tools enabling, in its final release, both the off-line as an Excel-based tool and the on-line web-tool functionality of the systems.

Strengths and weaknesses

Strengths	Weaknesses
▪ Structured approach to problem solving. ▪ Summary of multiple information.	▪ DSS complexity requires high levels of expertise for application. ▪ Datasets availability often constitutes

▪ Integration of multiple data sources. ▪ Enhances the effectiveness of the decision-making process. ▪ Improvement of interpersonal communication, active participation and consensus building. ▪ Inclusion of uncertainty analysis. ▪ Identifying preferred options for further discussion. ▪ Social, economic, biophysical and legislation trade-offs are required. ▪ Flexibility and adaptability to accommodate changes in the environment and decision-making approach. ▪ Promotes learning.	a limiting factor for wider application. ▪ Users find the system too detailed, time consuming and costly to use. ▪ Involvement of end-users and stakeholders are required to encourage application of DSS results in the final decision-making stage. ▪ No end user input is typically required before and during the DSS development.

Suitability for rapid assessment

Rapid use of the DSSs can be applied once initial data are obtained, however a long-term study is required for the collection and pre-processing of the input data. Further, existing DSSs are usually developed for research purposes and are not directly accessible to the public. They also require medium-to-high levels of expertise and scientific knowledge on the topic to be investigated.

Research gaps

Key research gaps relate to:

- Many DSSs are often prototypes demonstrated in relevant environments and developed for a specific case study. This highlights significant constraints regarding data requirements and their customization to new geographical regions.
- The analysis and inter-comparison of risks for different impacts and elements at risk are not supported.
- They often offer a sectoral perspective on physical or environmental issues yet neglect to provide a holistic overview of multi-hazard risk scenarios given they do not provide information regarding the interactions between different hazards.
- They are usually developed for research purposes and are not directly accessible to the public, and thus require medium to high levels of technical and scientific expertise for their application.
- Except for in limited situations, the design and application of the DSS does not engage with stakeholders and policy requirements.

5.4 Real option analysis

Real Options Analysis (ROA) is decision support approach which is particularly applicable to decision making under uncertainty. It quantifies the investment risk associated with uncertain future outcomes. It is particularly useful when considering the value of flexibility of investments, either with regard to the timing of the capital investment or the flexibility to adjust the investment as it progresses over time, i.e. allowing a project to adapt, expand or scale-back in response to unfolding events.

Users and application

End users of this tool are:

	European	National	Local/project
Policy and public decision makers	x	x	x
Investment, finance and insurance.	x	x	x
Business and industry (private sector).	x	x	x
Research	x	x	x
Civil society and NGOs.			

ROA can be used to appraise detailed adaptation options:

- Step 4: Assessing adaptation options.

Real Options Analysis is a decision support tool and can be used to support decision making through prioritising options or justify adaptation investment strategies using economic criteria. It can support the assessment of decisions such as the optimal timing for investment or whether to invest in options that offer greater flexibility in the future.

ROA is more appropriate for use at the project level, rather than strategic or national level, and is particularly useful in considering large-scale, long-term and costly adaptation interventions, such as dyke flood protection or dam-based water storage. ROA can be used to support the scoping of such adaptation intervention projects, the value of securing investments for future development, how to incorporate flexibility into the design of interventions and how the project value will evolve over stages of development. ROA is most likely to be supportive of projects that have some combination of substantial near-term benefits and the ability to scale-up or down in line with learning and new knowledge. This is applicable, for example, for situations where there is an existing adaptation deficit that the immediate investment can reduce, such as current flood risks.

The outputs are in the form of expected net present value, highlighting the economic efficiency of alternative options and thereby supporting the prioritization of options.

Model and tool methodology

Options analysis derives from the financial markets, where it has been used to assess the valuation of financial options and risk transfer. The same insights are also useful when there is risk or uncertainty involved with investment in physical assets, hence 'real' options. This has led to development of tools for ROA.

ROA quantifies the investment risk with uncertain future outcomes. This is useful when considering the value of flexibility with respect to the timing of capital investment, or adjustment of the investment over time in a number of decision point stages in response to unfolding events. This supports the consideration of flexibility, learning and future information (option values). In the adaptation context, it can be used to assess whether there is value in waiting for (climate) uncertainties to be resolved to avoid negative outcomes and to assess whether investing in adaptation solutions with greater flexibility are preferable while trading off the additional costs involved. It involves formal economic quantitative analysis based on an extended cost-benefit analysis and is applicable at the project level. In the adaptation domain, ROA tends to be most relevant for large capital-intensive projects, such as flood protection, and consequently, it has been used extensively to analyse coastal protection.

ROA can be conducted using a variety of methods. The most applicable to climate adaptation is dynamic programming, which is principally an extension of decision-tree analysis where nodes represent risk events that could occur in the future and each branch is associated with one possible outcome. Following this approach, the ROA value can be compared to a standard economic (cost-benefit) calculation that would provide a probability-weighted average of the outcomes along each possible branch in the tree. For an outline of the method and case study examples, see Watkiss *et al.* (2013).

Assumptions

The application requires inputs related to probability or probabilistic-like assumptions for climate change and the identification of decision points. It may not, therefore, be applicable under situations of deep uncertainty, where probabilistic information is low or missing. The derivation of probabilities for climate information is a major assumption, especially where this involves scenario uncertainty, such as different RCPs, and there is some form of assumption needed to derive a probability from an ensemble of climate models and scenarios. It also requires the identification of decision points for dynamic aspects of climate change and needs to match these decision points with appropriate climate data.

Model verification

It is challenging to verify these approaches, especially as they use probabilistic future climate projections.

Input data

Input data includes probabilistic climate information, however the specific metrics required will vary for each investment. Other socio-economic data requirements include the costs and benefits of relevance for the investment.

Outputs

The results of a full ROA are the expected net present values for adaptation options across a range of possible outcomes.

There is a reasonable body of ROA applications, however these predominately focus on coastal investment and protection. For example, Scandizzo (2011) applied ROA to assess the value of hard infrastructure, restoration of mangroves and coastal zone management options, concluding that ROA highlights the value of gradual and modular options. Similarly, van der Pol *et al.* (2013), Linquiti and Vonortas (2012) and Kontogianni *et al.* (2013) applied ROA to coastal assessments, highlighting the benefits of flexibility and/or learning. There have also been applications to port infrastructure using adaptive management approaches and a limited number of applications to other sectors. Examples include:

Dobes (2008, 2010)	Real options in the Mekong Delta, Vietnam, with a comparison of net present values of two housing alternatives with the option for houses with raisable floors.
Scandizzo (2011)	ROA to assess value of hard infrastructure, restoration of mangroves and coastal zone management options in Mexico.
Linquiti and Vonortas (2012)	ROA to assess investments in coastal protection using real options with case studies in Dhaka and Dar-es-Salaam.
Kontogianni *et al.* (2013)	ROA for value of maintaining flexibility: scaling up or down, deferral, acceleration or abandonment, to engineered structures in Greece.
Gersonius *et al.* (2013)	ROA for urban drainage infrastructure in England.
Dawson *et al.* (2018)	ROA of railways investment for Dawlish in the UK.
Woodward *et al.* (2014)	Considers the optimal time for investment in flood risk strategies for the Thames Estuary (UK) using RAO to assess flexible adaptive measures for potential flood risk management.
Jeuland and Whittington (2014)	ROA to water investment planning on the Blue Nile to identify flexibility in design and operating decisions for a series of large dams.
van der Pol *et al.* (2013)	ROA for Dike Investments.
Skourtos *et al.* (2016)	ROA for city of Bilboa.
Dittrich *et al.* (2018)	ROA for forestry.

Strengths and weaknesses

Strengths	Weaknesses
Supports quantitative economic analysis of the value of flexibility and learning for large adaptation investments.	A complex method which requires expert input and significant data requirements and resources.

Provides a structured method to conceptualise and visualise the concept of adaptive management.	Requires probabilistic climate information and quantitative impact data. Requirement for quantitative and monetised information on costs and benefits. Identification of decision points is complex for dynamic aspects of climate change and needs to match these decision points to equivalent climate data.

Suitability for rapid assessment

Previous studies can provide information regarding possible options of delay or flexibility, through there may be questions as to the appropriateness of transferability.

ROA uses a complex methodology which typically requires high volumes of data and resources. A more qualitative approach combined with the use of decision trees can be conducted, which is beneficial when significant amounts of data are unavailable. There are some examples of simple excel sheets for guidance,[67] however these also require considerable primary information to support analysis.

Research gaps

Research gaps include:

- Probabilistic climate projections and methods for deriving these.
- Light touch models, including decision trees, and excel based formats.
- Additional applications with subsequent evaluation and comparisons.
- A greater number of applied cases, including the issues associated with implementation and challenges of long-term monitoring for governance and financing.

[67] https://econadapt-toolbox.eu/tool-real-options-analysis#overlay-context=real-options-analysis

5.5 Robust decision making and decision scaling

Robust decision making (RDM) is an approach for decision making under deep uncertainty (DMDU). RDM aims to identify robust options or strategies, i.e. those which perform well over a wide range of future uncertainty. It does this by systematically exploring the consequences of choices, tested against data and models that simulate a large range of relevant scenarios (Lempert, 2019).

Based on robustness principles, Decision Scaling (DS) identifies Performance Indicators (PIs) of most relevance for decisions or investments and examines how these are affected by current climate. It subsequently uses similar sampling of a wide range of future climate uncertainty to stress test performance and identify more robust options (Brown, 2011).

Users and application

End users include:

	European	National	Local/Project
Policy and public decision makers		x	x
Investment, finance and insurance.			x
Business and industry (private sector).			
Research		x	x
Civil society and NGOs.			

RDM and DS are applied to the policy cycles at steps:

- Step 1: Preparing the ground for adaptation - all applications of RDM and DS start with setting objectives and related decision metric collaboratively.
- Step 2: Assessing risks and vulnerability to climate change – An extensive exploration of the vulnerability of the current status quo under various scenarios is usually part of the RDM and DS analysis.
- Step 4: Assessing adaptation options – assessing and comparing different alternatives is the main application of RDM and DS.

RDM has been applied as an analytical based decision support tool for identifying and prioritising adaptation options and scenarios. It is particularly relevant in situations of deep uncertainty. RDM is premised on the concept of "robustness" rather than "optimality" and the approach can help decision makers make more informed near-term decisions which have long-term consequences. It therefore offers an alternative to a conventional cost-benefit analysis, which identifies optimal options on the basis of economic efficiency.

RDM application has been particularly advanced in the water domain, especially at the catchment or project level, for example, within regional water management plans (Lempert and Groves, 2010), Flood Risk Management (Lempert *et al.*, 2013), dam dimensioning (Nassopoulos *et al.*, 2012) and coastal management plans (Groves and Sharon, 2013). RDM provides decision-makers with a set of adaptation options or strategies which tend to focus on low and no-regret measures as part of an iterative plan that can evolve over time with additional investments. By doing so, the RDM process can subsequently determine if an adaptive approach improves the performance and reduces the cost of the strategy across a wide range of futures (Groves *et al.*, 2019).

Decision Scaling uses similar principles to RDM, although there are differences. It seeks to test the relative performance and vulnerabilities of alternative system designs, focusing on their key performance indicators (Brown *et al.*, 2012). It develops response functions to map the performance of these indicators in the current climate and subsequently stress tests against future climate uncertainty. It has also been primarily adopted in the water sector, particularly for hydro-electricity power plants (Bonzanigo *et al.*, 2015; Grijsen *et al.*, 2014). Decision Scaling is incorporated as a method within the World Bank's decision tree framework for confronting climate uncertainty in Water Resource Planning and Project Design (Ray and Brown, 2015) and is a major part of the approach in Climate Risk Informed Decision Analysis (CRIDA) (Mendoza *et al.*, 2018). The Decision Tree Framework supports the assessment of climate risk in water projects in order to introduce adjustments or climate risk management plans for increasing robustness. The CRIDA framework complements the typical water resource planning process by assessing additional adaptive measures compared to a non-robust alternative.

RDM provides information (model output) on the performance, and thus attractiveness, of one or more options or strategies against uncertainty. Some applications extend this to provide multi-objective trade-off curves for each climate-relevant scenario (Lempert, 2019). It can also be used to provide an adaptive plan, which includes a multi-year schedule of investments and policies, keys trends to monitor and updates to enact if particular trends are observed (Lempert *et al.*, 2013). Decision Scaling aims at providing an answer to a fundamental question: 'is the climate that favours action A more or less likely than the climate that favours action B?' (Brown *et al.*, 2012). Decision scaling also provide information (model output) on the performance and attractiveness of options or strategies under uncertainty. It also creates a decision system model that simulates system performance as a function of climate inputs. The identification of risks in the design/system is based upon "climate response functions" which link performance indicators to climate variables and thus can focus the analysis of highly decision relevant metrics.

Model and tool methodology

While RDM can be used as a generic approach, most of the literature applications have used a highly formalised modelling-based approach. This involves the combination of both qualitative and quantitative information through a human and computer-guided modelling interface (Groves and Lempert, 2007). This computer-based analysis allows RDM to evaluate how different strategies perform under large ensembles, often of thousands or millions of runs, which reflect different plausible future conditions. Combinations of uncertainty parameters that are most important to the choice between strategies are statistically derived, and a summary of key trade-offs among promising strategies developed (Groves *et al.*, 2008). The identification of robust decisions emerges from this process of "deliberation with analysis". The steps are summarized in figure 9.

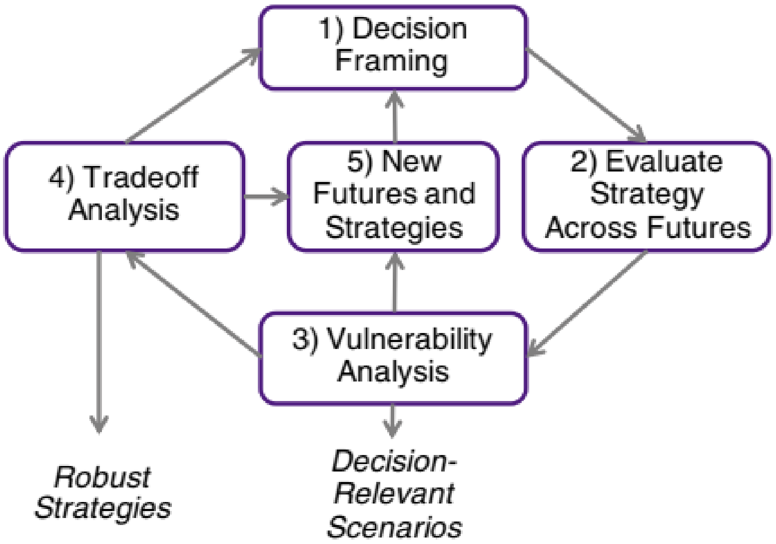

Figure 9: Steps in an RDM analysis. Source (Lempert, 2019, p. 31).

1. Decision framing: Stakeholders define the objective along with alternative actions that pursue the objective. They also identify uncertainties that might compromise the consequences of actions and the relationship between actions, uncertainties and objectives. In an interactive process, the action-uncertainty-objectives are updated from the identification of trade-offs or the definition of new futures and strategies.

2. Evaluate strategy across futures: At this stage, decision-makers propose strategies and evaluate them for each of the multiple plausible future paths. Strategies proposed can be defined by preferences of decision-makers and can also consider a range of strategies from a logical spectrum of available alternatives, of which these can constitute the outcome of the iterative RDM process. The evaluation follows the principles of a stress test, making explicit under which circumstances (thresholds) the strategy would fail. The ensemble of futures should be as diverse as possible for conducting stress tests.

3. Vulnerability analysis: Vulnerability analysis visualises and presents data analytics resulting from the stress test in order that users can distinguish futures in which proposed strategies meet or miss their goals. This stage therefore supports the identification of relevant scenarios that highlight the vulnerability of proposed strategies.

4. Trade-off analysis: This stage uses the scenarios from the vulnerability analysis to make explicit the trade-offs between strategies. Typically, the trade-offs are plotted in two displays. In one display, the performance of one or more strategies is plotted as a function of the likelihood of the policy-relevant scenarios. It supports users to explicitly state their underlying judgments regarding how the future would unfold when choosing one strategy over alternatives. The second display plots multi-objective trade-off curves (safety vs cost) for each policy-relevant scenario. This display helps users to judge competitive objectives per relevant scenario.

5. New future and strategies: In the final stage, decision-makers define greater robust strategies, rather than optimal strategies, based on vulnerability and trade-off analysis. Robust strategies perform well, compared to the alternatives, over a wide range of plausible futures. The new strategies usually incorporate additional policy levers that constitute the components of adaptative decision strategies in short-term non-regret actions, signposts and contingent actions to be taken if the pre-designated signpost signals are observed.

There are also simpler applications of RDM which use the general principles of uncertainty testing but do not use the large computer and algorithm-driven approach of above. These include applications which only test uncertainty around climate futures, such as looking for options or strategies that perform well against future multi-model climate ensemble information.

Decision scaling is an approach for climate risk assessment that links bottom-up vulnerability assessments with multiple sources of climate information (Brown, 2011). It typically uses a series of steps, identifying and defining Performance Indicators (PIs) and acceptable thresholds for decisions or investments. It subsequently assesses the performance of the PIs to current climate and climate variability and develops climate response functions. Finally, it analyses risks to PIs from the full ensemble of future climate models to stress test performance. The method aims to make the best use of uncertain, but potentially useful, climate information.

Table 8 draws a parallel between the original RDM formulation, decision scaling and decision tree framework for water resource projects and CRIDA.

Table 8: Methodological steps for RDM, decision scaling, decision tree framework and CRIDA.

RDM (Lempert, 2019)	Decision scaling (Brown *et al.*, 2012)	Decision tree framework (Ray and Brown, 2015)	CRIDA (Mendoza *et al.*, 2018).
Decision framing	**Identification of climate concerns, hazards, and thresholds.** Creation of a decision system model that simulates system performance as a function of climate inputs.	**Project screening:** Objectives, performance thresholds, uncertainties and connections to define whether it is climate sensitive.	**Decision context:** Performance metrics, critical thresholds, external drivers and water resource system models
		Initial analysis: Rapid project scoping to assess if the climate is a dominant risk factor	

Evaluate strategies across futures	**Identifying climate conditions that cause risks:** By means of a classic sensitivity analysis to identify problematic climate conditions, the parsing of the climate space according to optimal or best decisions and the development of a climate response function.	**Climate stress test:** Complete hydrologic-economic water modelling to identify climate sensitivity of the system within the range of climate-relevant scenarios.	**Bottom-up vulnerability assessment:** Stress test for performance limits; definition of future risk of unacceptable performance.
Vulnerability analysis	**Definition of climate states with decision model** according to the decision that dominates for that range of climate conditions. It clearly states the specific climate conditions that pose a risk or favour a particular decision.		
Trade-off analysis	**Climate informed risk estimation**: Based on climate states relating to decisions, the final stage is defining climate-informed probabilities associated with each state, with a goal of estimating which state is more probable than the other.		**Formulation of robust and flexible actions:** Robust plans and adaptation pathways development; comparing completeness, effectiveness and acceptability.
New future strategies		**Climate risk management:** Definition of direct adjustment in project formulation, Climate Risk Management Plan or advise to reconsider the project if there is a high risk.	**Evaluate plan alternatives:** Evaluation with respect to baseline and different future scenarios to inform a recommended plan.
			Institutionalise decisions: Implementation and monitoring plan considering institutions and finances.

Input data

RDM and DS were developed to manage deep uncertainties and make the best use of available information. Both try to draw on large climate data sets to support greater robust analysis of uncertainty. Due to the focus on addressing deep uncertainty, RDM eschews probabilities or prescribed sets of distributions, drawing on the concepts of imprecise probabilities (Lempert, 2019). DS makes use of all sources of climate information, for example, frequency analysis of GCM output, historical data, paleoclimatology data, stochastically generated climate simulations and expert judgment of scientists and stakeholders (Ray and Brown, 2015).

RDM and DS require the user to define objectives and performance metrics of strategies, projects, measures, which are subsequently assessed in terms of robustness. These strategies, projects and measures may be defined by policy agendas and stakeholder concerns, which might involve multi-sectoral objectives (Lempert, 2019) or for DS from analysis of project specific key performance indicators (Brown, 2011). For RDM, multiple sources of uncertainty, not just climate change, are often incorporated, which expands the input requirements for the analysis. Data sources for sectors such as water, agriculture and land use, transport, infrastructure, energy and natural resources are often coupled with economic cost-benefit analyses of candidate strategies (Bhave *et al.*, 2016).

Outputs

RDM aims at providing decision-relevant scenarios and robust strategies, which illuminate trade-offs among not-unreasonable choices. In some applications, these trade-offs are communicated to decision-makers by means of a scenario map, portraying when one or combined strategies dominate as a function of relevant scenarios probability (Lempert, 2019). For considering a larger number of strategies, an RDM analysis can provide a percentage of futures/ relevant scenarios in which objectives are not met by strategies considered (Groves *et al.*, 2019).

Decision scaling also provides information on decision-relevant options and strategies under uncertainty. In some applications, this is extended to produce cumulative distribution functions for key performance indicators, such as reliability, based on GCM projections. The output of the DS analysis can also be visualized as a decision map showing the robustness of decisions for policy or design. This information can be presented in a probabilistic form, including for alternative option choices noting uncertainties associated with climate change prevent estimating true probabilities.

RDM has been applied for California (Lempert and Groves, 2010) and the Colorado River Basin Water Resource Planning (Groves *et al.*, 2013, 2019). The latter case was a seven-state collaboration to identify water management strategies to reduce vulnerabilities in the Colorado River Basin. The system is increasingly threatened by rising demand and uncertainties of future supply. Hence, RDM was used to assess system vulnerabilities in relation to a wide range of objectives, such as water supply reliability, hydropower, ecosystem health and recreation. A robust strategy was defined as the one that minimises regret across a broad range of plausible future conditions. In turn, regret was the additional amount of total annual supply needed to maintain the reservoir level at 1000 feet across the simulation. The analysis concluded that there was no single robust choice, existing some trade-off in robustness for one range of conditions relative to another. Hence, the RDM insights were coupled with a Bayesian updating, modelling how an adaptive strategy would evolve in response to predefined triggers and new information about future conditions. The outcome of the process was a management strategy implementation pathway, guiding investments over the coming decade. Yet, the analysis suggested the existence of multiple plausible futures in which management strategies considered in the study would not be enough to ensure an acceptable outcome. Hence, new options should be evaluated along with additional interaction of the RDM analysis.

RDM was used for helping Ho Chi Minh City (Vietnam) for developing integrated flood risk management strategies in the face of deep uncertainty, being the fourth most threatened coastal city by climate change (Lempert *et al.*, 2013). The potential consequences of alternative flood risk management employed three measures of risk: the risk to the poor as expected people affected by annually flooding, the risk to the non-poor as expected people affected by annually flooding, and risk to economic value. Scenarios were defined by nine factors describing future and socio-economic conditions affecting hazards, exposure and vulnerability. Policies include alternative configuration of integrated flood risk management, including infrastructure, adaptation and retreat options. The baseline was a set of soon-to-be-completed infrastructure. According to the results, the baseline may reduce the risk in best estimates of future conditions, but it may not maintain a low risk in many other plausible futures. The analysis further suggested that adaptation and retreat measures, particularly when used adaptively, can play an important role in reducing this risk.

The water utility in Lima (Peru), SEDEPAL, considered a multi-billion-dollar Master Plan including 12 major infrastructure investments until 2040. As water supply depends primarily on precipitation in the upper watersheds, future changes in precipitation and droughts could compromise Lima's water availability. RDM was used by the World Bank for recommending and adaptive investment plan (Kalra *et al.*, 2015). The investments portfolios were compared in diverse climate scenarios, with the performance benchmark set as the 90th percentile of monthly met demand and whether this exceeded 90%. The results indicated that implementing all 14 projects could ensure water reliability in many, but not all, plausible futures. These results were subsequently assessed using budgetary scenarios (full, 75%, and 50%) for identifying portfolios that achieve the greatest water reliability under different project feasibility, demand and streamflow conditions. These portfolios were organised in a decision tree, guiding no-regret and adaptive investment decision. Overall, the analysis provide evidence that SEDEPAL could achieve the same degree of water reliability by implementing only 10 out of the 14 projects, resulting in a 25% to 50% cost savings depending on the favourability of demand and streamflow conditions.

Groves and Sharon (2013) applied RDM to support planning the future of Coastal Louisiana (Lempert *et al.*, 2013). Nassopoulos *et al.* (2012) applied the method to dam dimensioning and Mereu *et al.* (2018) applied RDM to the Agricultural Sector in Nigeria.

Decision scaling has been applied in the hydro sector and for water resources management: García *et al.* (2014) applied DS to water resources management, while Bonzanigo *et al.* (2015) applied DS to decision making in hydropower in Nepal and Grijsen *et al.* (2014) to the Niger River Basin Sustainable Development Action Plan.

Gilroy and Jeuken (2018) apply the CRIDA approach for water security planning in Central Cebu (Philippines) under climate change uncertainty. The primary objective of the CRIDA analysis was evaluating and communicating climate uncertainties to decision-makers, with the ambition to ensure the continuous availability of good quality water to all existing and future uses for a 25-year planning horizon. The main performance metric used for stress testing was unmet water demand (mcm/year), with a target threshold equal to 0 mcm/year at 97% reliability. A vulnerability assessment considered two climate change drivers (i) the combined impacts of changing annual temperatures and precipitation in an Aridity Index, and (ii) the change in precipitation from year to year. The results indicated that the current system is more sensitive to expected changes in demand than to climate change uncertainty within the selected planning horizon. The results suggest low future risk and variable analytical uncertainty, favouring expandable or reversible actions (flexibility over robustness). After the initial evaluation of actions and development of strategies, three strategies were presented using adaptation pathways to meet water demands in two phases (2020 and 2030). The estimation of the net present value of each pathway for diverse climate scenarios indicated that the most economically beneficial pathway for phase I was a non-regret option.

Strengths and weaknesses

Strengths	Weaknesses
▪ Ability to identify robust decisions in the face of deep uncertainty where probabilistic information is low or missing, or climate uncertainty is high. ▪ Analytical power of testing multiple options or strategies. ▪ DS – in addition, identification of main vulnerabilities and focus on performance indicators, i.e. on what matters. ▪ Often powerful visualizations supporting a shared vision. ▪ Based upon stakeholder decision metrics. ▪ Can work with physical or economic metrics, enhancing potential for application across non-market sectors.	▪ The informal application requires considerable time and resources. ▪ The formal application has a high demand for quantitative information, computing power and requires a high degree of expert knowledge. ▪ Multiple drivers and objectives lead to requiring integrated models which are not always available. ▪ Demand for technical skills, yet is also a time-consuming stakeholder processes. ▪ Because strategies have to be robust against worst-case scenarios, solutions often tend to be conservative (Bhave *et al.*, 2016). ▪ Can be subjective, influenced by stakeholders' perceptions.

Suitability for rapid assessment

RDM and DS are not applicable for rapid assessment due to the significant quantities of input data required. Further, formal application of the methods and models are not suitable for rapid assessment.

Research gaps

RDM relies heavily on known/expected thresholds, triggers and/or signposts for adaptive decisions. Future research is required to indicate how these thresholds are defined clearly, especially if they are unknown/poorly understood or unquantifiable (Reeder and Ranger, 2011).

There is a need for developing RDM-little through approaches such as expert elicitation and participatory modelling. Future research can better develop the integration of RDM with evolutionary algorithms for multi-objective robust optimisation. As differences in stakeholder opinion and political opposition to action often lead to policy paralysis, more research is needed to assess how the "deliberation with analysis" transform or reproduce different risk perceptions and attitudes regarding such objectives (Bhave *et al.*, 2016). There is also a need for further research and development on light-touch applications of the approach and simplified RDM models (Watkiss *et al.*, 2014).

More real-world applications are required to assess whether RDM robust options and low regret strategies are realistic and available, considering factors limiting their implementation such as legal constraints, transaction costs, lack of human capital and political will (Hallegatte, 2014). As above, the time, resources and technical knowledge for formal RDM is high and this constitutes a barrier to application – the need for light-touch applications of the approach and simplified RDM models.

5.6 Dynamic adaptive policy pathways

Dynamic Adaptive Policy Pathways (DAPP) is an approach for decision making under deep uncertainty (DMDU) that explicitly includes decision making over time. The essence is proactive and dynamic planning in response to how the future actually unfolds. It explores alternative sequences of decisions or actions of development or adaptation pathways under multiple futures and illuminates the path-dependency of options.

Users and application

End users of DAPP include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x		
Civil society and NGOs.			

These can be used for the policy cycle:

- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

DAPP can be used for the development of strategic plans for, for example, general water management (Delta Plans), adaptive flood risk management or climate change adaptation at the catchment, national or local/project level, as well as provide support regarding adaptation investment decisions at the national or local level.

Model and tool methodology

Decisions or actions have uncertain design lives and may fail to achieve their objectives as conditions change, for example, if they reach an adaptation tipping point, or they may not be feasibly implemented until certain conditions exist such as they reach an opportunity tipping point. Different pathways achieve the specified objectives under changing conditions, with these typically visualized in a Metro-map (figure 10) or a decision tree against a time or condition axis (figure 11).

Experience with DAPP has highlighted that this method is best applied in an iterative and stepwise fashion, with a gradually increasing level of detail and effort. Three levels have been identified, detailed in figure 12.

All levels of analysis can be supported by the use of the adaptation pathway generator tool[68] which is publicly available.

[68] https://publicwiki.deltares.nl/display/AP/Pathways+Generator

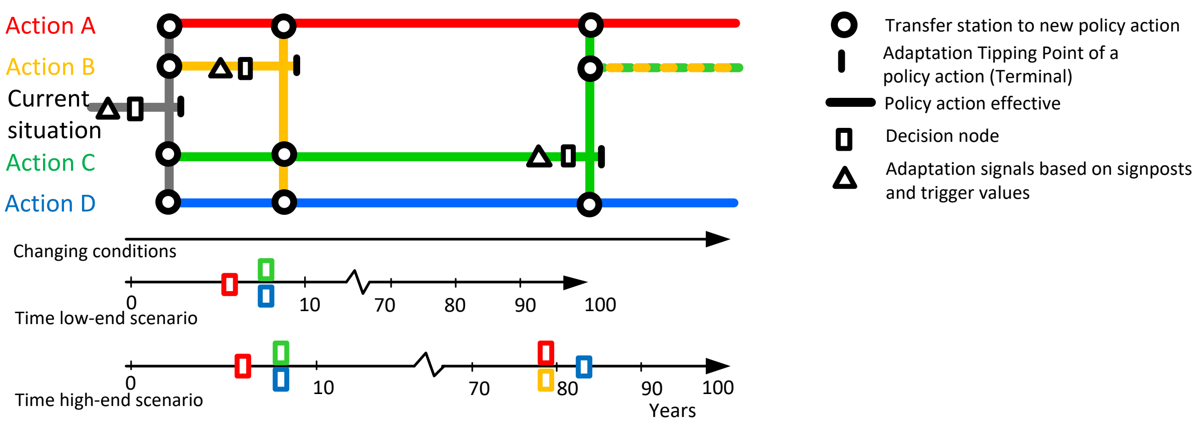

Figure 10: Metro map of adaptation pathways, from Haasnoot et al. (2013).

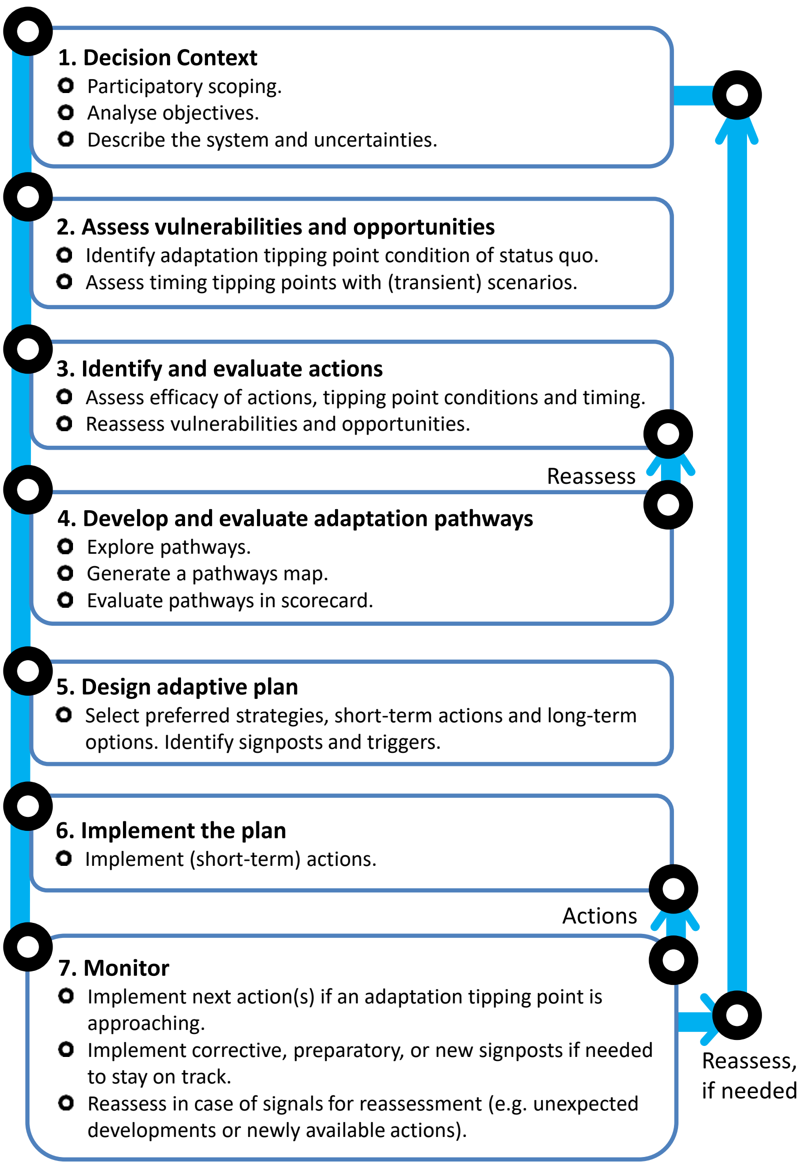

Figure 11: An example of a decision tree (Haasnoot et al., 2019).

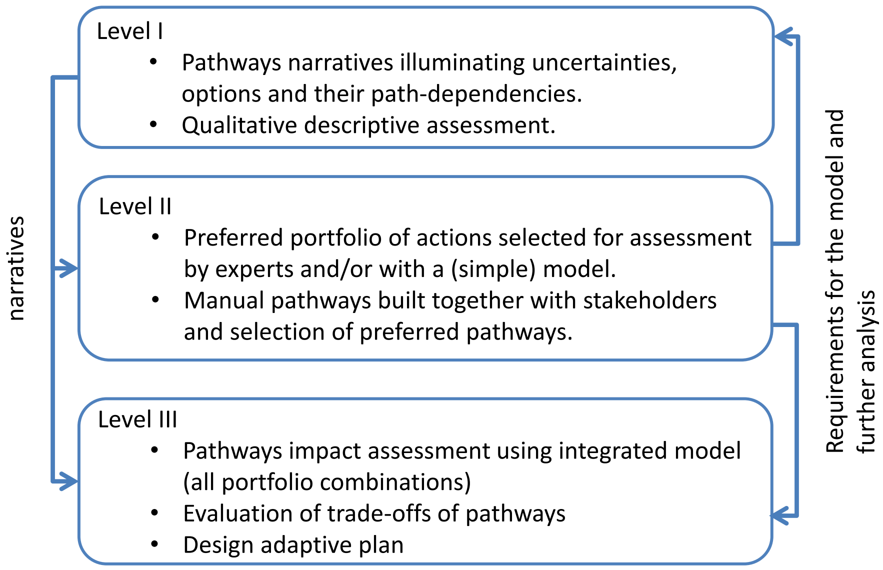

Figure 12: Levels of analysis, their output and purpose (Haasnoot et al., 2019).

Input data

For level I and II: Climate input data requirements include qualitative climate change over time and aggregated quantitative climate data for the system. For level III: detailed climate change projections to derive hydro-meteorological boundary conditions for numerical models from data sets such as CMIP5, CORDEX or national climate scenarios are required.

Possible socio-economic data are qualitative for levels I and II, quantitative for level III, include demographic scenarios; literature on strategic plans, previous assessments and model studies; indicators to quantify the performance of the system with stakeholder involvement; and possible future scenarios and risk mitigating actions, also incorporating stakeholder involvement.

Outputs

Outputs can include action plans, presented as metro-maps (figure 10) or decision trees (figure 11). Different decision pathways with possible short-term actions and long-term options and the adaptation signals to identify when to implement actions or revisit decisions can be detailed.

Examples where DAPPs have been applied include:

- The Netherlands: Dutch Delta Programme (Bloemen *et al.*, 2018; Zandvoort *et al.*, 2017).
- Bangladesh: Bangladesh Delta Plan 2100.[69]
- EU-FP7: RISES-AM (Responses to coastal climate change: Innovative Strategies for high End Scenarios – Adaptation and Mitigation) research project, developing generic pathways for responses to sea-level rise and extreme storm impacts at local and regional levels (Haasnoot *et al.*, 2019a).
- Philippines: Economic Analysis Integrating Uncertainty into Adaptation Investment Decisions (Haasnoot *et al.*, 2019b).

[69] https://www.deltares.nl/en/projects/deltaplan-bangladesh-2/

- United States: Miami flood resilience and San Francisco water supply.
- New Zealand: application of pathways in coastal zone adaptation planning (Lawrence and Haasnoot, 2017).
- Thailand: Development of a Flood Early Warning System and an Adaptive Flood Risk Management plan for Sukhothai district / Yom River Basin.

These adaptation pathways concepts have been successfully adopted and applied by various institutions worldwide, including the UK for the Thames Barrier, US, Denmark, Portugal, Australia and New Zealand.

Strengths and weaknesses

Strengths	Weaknesses
▪ The DAPP process yields a plan for action. This describes which actions to take in the short-term to meet policy objectives and maintain the availability of long-term options. This can develop monitoring and under which conditions further actions should be taken to maintain policy targets. ▪ DAPP is a flexible, generic analytical approach which is often initially conducted qualitatively based on expert judgement, followed by a greater detailed model-based assessment. ▪ Flexibility: Where resources and data permit, model-based assessments can be used to establish tipping points and pathways, for example, for stress testing, sensitivity analyses and ensemble generation. In the absence of models or reliable quantitative data, expert judgement and greater qualitative assessments can be applied with local experts and stakeholders. When objectives cannot be translated into clear target indicators and values, relative values can be used.	▪ The adaptive approach is an alternative method with respect to conventional planning. Stakeholders and decision makers will be required to familiarize themselves with this novel approach.

Suitability for rapid assessment

DAPP can only be applied for rapid assessment in case of a level I analysis, in which the pathways are developed during interactive stakeholder sessions using predominately qualitative information.

Research gaps

The application of DAPPs can be conceptually complex. Therefore, smart methods for introducing the concept of DAPP are required. A game has been developed for this purpose[70] which can be applied within the context of river basins management and coastal protection. This could be extended for other application contexts.

[70] http://deltagame.deltares.nl

5.7 Urban adaptation tools and decision frameworks

This section focuses on general tools for urban adaptation, which complements section 2.8 on cities and urban areas (Chapter 2: Impact and climate adaptation models) and can be applied in conjunction with hazard, exposure and vulnerability models of chapter 1, such as coastal and river flood models. This section focuses on:

- Urban adaptation tools and frameworks.
- Information portals, data bases and look up tables, such as for adaptation and costs.
- Urban adaptation case studies and good practice examples.

Users and application

End users of these models include:

	European	National	Local/Project
Policy and public decision makers	x	x	x
Investment, finance and insurance.			
Business and industry (private sector).			
Research	x	x	x
Civil society and NGOs.			

These models can be applied to assess various stages of adaptation policy and decision making:

- Step 2: Assessing risks and vulnerability to climate change
- Step 3: Identifying adaptation options
- Step 4: Assessing adaptation options

However, their primary focus is on identifying adaptation options (Step 2) and undertaking some initial prioritisation to assess options (Step 3).

There are a variety of different support tools available:

Urban adaptation tools and framework: This set of tools and models includes guiding principles or frameworks to support the development of adaptation plans and prioritisation. These include frameworks that align with the EEA adaptation policy cycle but focused on the urban scale, such as the Urban Adaptation Support Tool. It may also include guidance or frameworks for specific methods, such as transformative adaptation pathways as with the RAMSES transition handbook. Many of these tools are guidance documents or workbooks/templates that can support urban authorities/ city scale organisations through key adaptation steps.

Information portals, databases and look up tables: This set of tools provides information on key adaptation options, often in conjunction with look up tables on options, costs and occasionally the benefits of adaptation tailored to urban settings. An example is the RESIN project tool.[71]

[71] https://resin-cities.eu/resources/

Urban adaptation case studies and good practice examples: This set of tools and models includes case studies and good practice examples that provide information on successful urban adaptation projects which can be used to support other cities. Examples include the BASE and EEA urban adaptation studies.

Model and tool methodology

Examples of urban adaptation tools and frameworks include:

Urban adaptation support tool

The aim of the Urban Adaptation Support Tool[72] (UAST) is to assist cities, towns and other local authorities in developing, implementing and monitoring climate change adaptation plans. UAST was developed as a practical guidance for urban areas in recognition of their importance in the European economy. The Urban Adaptation Support Tool outlines detailed guidance of required steps to develop and implement an adaptation strategy, referencing guidance materials and tools. The tool offers valuable support to both the cities that are just starting on the adaptation planning and to those more advanced in the adaptation process.

RAMSES

RAMSES[73] was a European research project which aimed to deliver quantified evidence of the impacts of climate change and the costs and benefits of a wide range of adaptation measures, focusing on cities. RAMSES engaged with stakeholders to ensure this information was policy relevant and ultimately enabled the design and implementation of adaptation strategies in the EU and beyond. It includes the Transition Handbook and the Training Package to support cities in their adaptation work. The Transition Handbook embeds the most important findings from the project in a process management cycle, using the Urban Adaptation Support Tool developed by the European Environment Agency, and synthetises the project results in a practical step-by-step fashion, presenting resources that cities can use to strengthen their knowledge of climate adaptation planning. The Training Package complements the Transition Handbook by examining existing toolkits to support adaptation management in cities and proposes worksheets and exercises that cities can use to progress on their adaptation endeavours. The worksheets complement the information contained in the Transition Handbook and offer cities a clear path towards developing their adaptation to climate change.

RESIN - climate resilient cities and infrastructures

RESIN[74] is an interdisciplinary, practice-based research project investigating climate resilience in European cities. Through co-creation and knowledge brokerage between cities and researchers, the project is working on developing practical and applicable tools to support cities in designing and implementing climate adaptation strategies for their local contexts. The project aims to compare and evaluate the methods that can be used to plan for climate adaptation in order to progress formal standardisation of

[72] https://climate-adapt.eea.europa.eu/knowledge/tools/urban-ast/step-0-0
[73] https://ramses-cities.eu/home/
[74] https://resin-cities.eu/home/

adaptation strategies. The project has produced a user guide[75] for climate change adaptation, which is based around the policy cycle.

Information portals, databases and look up tables

Examples include:

ECONADAPT:[76] This was a European Commission 7th Research Framework Programme (FP7) project striving to support adaptation planning though developing the knowledge base on the economics of adaptation to climate change and converting this into practical information for decision makers. It includes a web-based inventory of studies on the costs and benefits of adaptation and a toolbox,[77] which provides easily accessible information regarding the economic assessment of adaptation, including a database of costs and benefits for a selection of options.

RESIN – adaptation options library: RESIN[78] has produced an adaptation library/ database which includes look up tables on urban adaptation. This provides information on options against a number of criteria, including hazards, application scale, effectiveness and cost-efficiency.

Urban adaptation case studies and examples

Examples include:

BASE:[79] The EU research project "Bottom-Up Climate Adaptation Strategies Towards a Sustainable Europe" (BASE) supported action for sustainable climate change adaptation in Europe. BASE included experiential and scientific information on adaptation meaningful, transferable and easily accessible to decision makers at all levels. The project was funded under the EU FP7. It includes a large number of project case studies, many of which are urban. The project published *BASE Adaptation Inspiration Book: 23 European Cases of Climate Change Adaptation*[80] in conjunction with additional outputs and videos.[81]

European Environment Agency Climate-ADAPT: There is a significant quantity of literature within the urban sector of the Climate-ADAPT database. This includes publications and reports, information portals, indicators, guidance, tools, research and knowledge projects, adaptation options, case studies and organisations.

This includes the Urban Adaptation Map Viewer.[82] The aim of the map viewer is to provide an overview of the current and future climate hazards facing the European cities, the vulnerability of the cities to these hazards and their adaptive capacity. The map viewer collates information from various sources on the observed and projected spatial distribution and intensity of high temperatures, flooding, water scarcity and

[75] https://resin-cities.eu/fileadmin/user_upload/Handbooks/RESIN-D4-3-guide-ENGLISH-www.pdf
[76] https://econadapt-toolbox.eu/
[77] https://econadapt-toolbox.eu/data-sources
[78] https://resin.vmz.services/apps/adaptation/v4/#!/login?redirect=%2Fapp%2Fsummary
[79] https://base-adaptation.eu/
[80] https://base-adaptation.eu/sites/default/files/BASE%20Inspiration%20Book.pdf
[81] https://base-adaptation.eu/base-project-results
[82] https://climate-adapt.eea.europa.eu/knowledge/tools/urban-adaptation

wildfires. It also provides some information on the causes of cities' vulnerability and exposure to these hazards, linked to the characteristics of cities and their population. Finally, the map viewer provides information regarding adaptation planning and actions of European cities. The information contained in the maps, combined with the Urban Audit City Factsheets, supports the development of understanding regarding the current and projected climate impacts in European cities. It is also possible to compare individual cities and to identify other cities in similar situations. Additional sources of information, illustrative case studies and relevant indicators are suggested for further learning regarding the climate risks to European cities.

There are a large number of Climate-ADAPT case studies,[83] an EEA Case studies search tool[84] and EEA Case studies booklet.[85]

RAMSES common platform / city module - city navigator:[86] RAMSES project results are publicly available via the RAMSES Common Platform. The online platform helps to share results among partners and the wider research community. The Common Platform has been developed for interested scientists, experts and the general public. The goal is to present the data and results of RAMSES in an attractive manner through different visualizations. Scientific target groups include various fields and levels of expertise. Interested laypeople are also invited to access the platform to develop understanding regarding advancements in impact and adaptation science for cities. It is possible to view results of the RAMSES project for over 600 European cities. The platform is regularly updated to include new findings. There are additionally a large number of study publications and videos.[87]

Other projects that have relevance content include:

RESCCUE (RESilience to cope with Climate Change in Urban areas):[88] a multi-sectoral approach focusing on water. The RESCCUE project aims to support urban areas globally to become more resilient to climate change. RESCCUE will bring this objective to practice by providing innovative tools and models to improve the ability of cities to withstand and recover quickly from multiple shocks and stresses and maintain continuity of services. An end-users-oriented toolkit, predominantly for city managers and urban service operators, will have the capability to be deployed to different types of cities, with different climate change pressures.

Smart mature resilience: For more resilient European cities, Smart Mature Resilience (SMR)[89] is a multi-disciplinary research project. Here, researchers and cities collaborate to enhance cities' capacity to resist, absorb and recover from the hazardous effects of climate change. SMR has been working for just over two years to develop a suite of tools to help cities enhance their resilience. These tools have been developed in close cooperation between seven partner cities: Glasgow, San Sebastian,

[83] https://climate-adapt.eea.europa.eu/knowledge/tools/case-studies-climate-adapt/
[84] https://climate-adapt.eea.europa.eu/knowledge/sat
[85] https://climate-adapt.eea.europa.eu/about/climate-adapt-10-case-studies-online.pdf
[86] http://www.pik-potsdam.de/~kriewald/ramses/
[87] https://ramses-cities.eu/resources/#c446
[88] http://www.resccue.eu/
[89] https://smr-project.eu/home/

Kristiansand, Rome, Riga, Bristol and Vejle; SMR's four university partners; ICLEI Europe and standardization body DIN.

EPICURO (European partnership for urban resilience):[90] EPICURO's scope aims to foster multi-actor transnational cooperation and enhance knowledge regarding technology solutions available to local communities, as well as to increase Civil Protection teams' specialisation and enhance policy and institutional commitment for increasing public support and citizens' capacities for building resilience within their communities.

Assumptions

The main assumption with these approaches is the degree to which information is transferable between locations and climate change risk.

Model verification

These is some potential to verify information based on ex post analysis of adaptation options, as implemented.

Input data

Climate input data requirements vary according to the method and approach. The socio-economic data requirements will depend on the adaptation options and tool but it is likely to require some city scale information of relevance for adaptation, such as demographics.

Outputs

These vary with the tool but is likely to be in the form of additional information on putting plans in place or information of relevance for potential options.

Strengths and weaknesses

Strengths	Weaknesses
Provide concise and readily available information of relevance for developing adaptation plans or considering options.	Key issues over transferability of information between cities.
	Information is often generic and does not account for location or context. May not be detailed enough for detailed analysis and prioritisation of adaptation.

Suitability for rapid assessment

These tools are specifically designed to provide access to previous data quickly and for early planning or rapid use of available information to help early adaptation planning.

[90] http://www.epicurocp.eu/

Research gaps

Key research gaps mainly relate to:

- Many urban DSSs are often developed and tested for a specific urban location. There are often data constraints, as well as questions regarding their transferability, when being applied to new geographical locations. Improved sources of open access data are needed for wider application, along with better understanding of the applicability and limits of transferability.
- More formalised tools are usually developed for research purposes and are not easily accessible to the public, requiring medium-high levels of technical and scientific expertise for their application. There is a research gap on rapid assessment tools.
- Adaptation at the city level often involves integration of climate risks and adaptation responses alongside other urban priorities and plans. There is a research gap on how to address these competing aspects in policy relevant applications to enable climate mainstreaming.

Chapter 6.0: Future research

This section provides a "gap analysis" to guide future research regarding the model and tool group methodologies, but not at the single model level, based on the literature reviewed within this comprehensive desk review. Gaps are grouped into four main categories:

1. Gaps in data availability, accessibility, analysis and processing
2. Gaps in addressing dynamics and feedbacks
3. Gaps in model coupling
4. Gaps in decision support.

A further category, 'Gaps in policy support' are identified as areas of research which have not been fully developed across the policy cycle. As such, this literature is largely missing from this review.

6.1 Gaps in data availability, accessibility, analysis and processing

Resolution and completeness of data from climate models and scenarios: The spatial and temporal resolution of Global Circulation Models (GCMs) has increased the confidence of climatic projections, providing greater accuracy in simulations of extreme events (Giorgi *et al.*, 2014). Nevertheless, the resolution of GCMs and even Regional Climate Models (RCMs) (10-30 km) is generally too coarse to usefully support several adaptation assessments. An example is their inability to capture sub-daily extreme events that are needed for a large number of "local" adaptation assessments (Ban *et al.*, 2015). This issue is addressed by applying downscaling techniques and bias corrections, but uncertainty remains large in these methods. In the specific field of the prediction of spatially and temporally localized (sub daily scale) intense precipitations, some advancements are expected from a new generation of Convection Permitting (CP) RCMs. These are being currently investigated by different projects such as the H2020 EUCP and initiatives including FPS CORDEX CP.

Usability of online services: Online services to analyze climate data have become increasingly popular in research over the last five years. A topical example is the Climate Explorer from the Royal Netherland Meteorological Institute (KNMI). It allows users to select a specific indicator, such as 'monthly mean temperature' for a user-defined area, and subsequently generates a time series for that area. However, due to the significant volume of data that needs to be downloaded for the calculation of the indicators, these services are mostly addressed to scientists and of difficult usability for end-users in the policy domain. Other services, such as data from the Expert Team on Climate Change Detection and Indices (ETCCDI), lack some specific variables such as wind, snow and humidity. There are thus some actions required in order to improve the accessibility and diffusion of these tools: (1) the current systems need to be upgraded to enable the handling of large amounts of data, (2) the websites with the software need to be developed such that they become more attractive for policy makers and enable access to rapid assessment tools, (3) future applications of services should constantly expand the variables considered.

Resolution and completeness of data for hazard assessments: Despite the significant growth in hazard data from, for example, remote sensing, data quality and time series lengths are not always sufficient. This, for instance, applies to hydrologic models that require a large enough dataset of observations for adequate calibration and validation. The same issue is reported in heatwave research, where it appears that the assessment of heatwave events and their trends lack long-term data records with, in particular, many European regions having no or sparse in-situ data.

A similar problem affects the spatial resolution of data. Hydrological models offer again an example: they require land use data with $<30m^2$ granularity, however most of the relevant information is available at $1km^2$, too low a resolution to address hydrodynamic processes. Other models require specific data pertaining to a particular event in order to accurately replicate such an event, such as water level changes during a period of hours or days. More event-based data are required to train such models. Vegetation models need more empirical data on species and factors which influence species' niche requirements (Mokany and Ferrier, 2011). This not only pertains to climate, but also to non-climate factors such as pollution, land degradation and habitat fragmentation (Bellard *et al.*, 2012).

The problem is that managing the huge amount of data required can rapidly become unfeasible. A solution could be to develop the use of flexible grids in order to use high resolution data only in those areas where it is needed. In this way, computation time remains manageable. Further development of remote sensing can complement observational measurements when missing. This avenue is particularly promising for local hydrological models, which require local precipitation data, as demonstrated by the RADKLIM dataset provided by the German Weather Service.

Resolution and completeness of data for exposure assessments: The exposure analysis requires the availability of future social economic data and it is thus strictly linked to the development of social economic scenarios. The Shared Socio-economic Pathways (SSPs) relating to GDP and population growth, are among those most used in the study of climate change. They are, however, specified at the "country level", which makes them less applicable for impact and adaptation analyses at regional to local levels. An increasing number of initiatives provide "downscaled" or gridded specification of SSPs (for instance, Murakami and Yamagata, 2016) but these are not yet of widespread use. By the same token, high resolution exposure data, especially on assets, is required. Although some databases, including PAGER, offer some information regarding building assets, these data are far from complete to enable local to regional assessments. New developments, such as Open Street Map, could offer new opportunities to map critical infrastructure.

Furthermore, the implementation and quantification of adaptation role in different scenario-building exercises is still less developed and consolidated than that of mitigation. These are all areas of research that deserve more effort and that can benefit the socio-economic modelling community.

Resolution and completeness of data for vulnerability assessments: Most socio-economic vulnerability data, including demographics, income and gender, required for adaptation studies is needed at the regional scales (regional, provincial or municipal administrative levels). Most of the social vulnerability indicators in Europe are available either at NUTS2 or NUTS3 administrative levels. This is already a great improvement compared to country aggregated data, however to perform analysis on finer resolutions, such as at municipal or local scales, developers have to either use the countries' census data, as demonstrated in Marzi *et al.* (2019) or peruse stakeholder-driven approaches (Linkov and Trump, 2019). More data is needed to validate vulnerability models. In addition, as highlighted in Marzi, Mysiak and Santato (2018), multiple scale vulnerability assessments could be more informative and useful for policy makers than scale-specific ones. There are few studies investigating socioeconomic vulnerability at several collective and community levels paying attention to scale-dependency issues.

Resolution and completeness of data for adaptation assessments: More information is required on the cost of adaptation. One of the main criticalities in this area is represented by the local nature of adaptation. Accordingly, while information can be available and gathered for specific actions and contexts, the extension of adaptation analyses that require aggregation at the wider scale, such as the regional, national or larger one, becomes challenging. There is a gap that still needs to be convincingly bridged between the huge aggregation in adaptation cost estimates, performed by Integrated Assessment Models or other macroeconomic models, and the more precise, but not generalizable, local analyses. A particular case of data limitations pertains to many insurance applications, limiting the study of insurance as an adaptation option. More specifically, there is limited data available for calibrating insurance pricing rules as well as for consumer decisions with regards to insurance purchases and whether to implement risk reduction measures. With a few exceptions (Hudson *et al.*, 2019), models often only focus on the impacts of climate change on the insurance sector. Instead, there is a need for a comprehensive integrated modelling framework of risk, insurance supply and demand and risk reduction behaviour.

6.2 Gaps in addressing dynamics and feedbacks

Impact interaction, extremes and temporal dynamics in hazard assessment: Hazard and adaptation assessments should consider the effect of multiple hazards. Just as examples: landslides are more easily triggered after a forest fire and during a flash flood event. However, the current hazard-impact models do not account for compound or consecutive multi-hazards (De Ruiter *et al.*, 2020). This is an issue, for instance, for desertification models, where the effect of different vegetation structures and species compositions should be greater integrated with models for erosion processes and land degradation/ conservation.

Another knowledge gap, generalised across many different impact areas, is the modeling and quantification of impacts from extreme events. This is the case, for example, of crop-modeling that still feature a limited understanding of the interactions among climate extremes, such as frost and heat, with changes in quality of crop production. Similarly, pests and diseases, phosphorus, nutrition and ozone effects need to be further explored and implemented in such models (Antle *et al.*, 2017).

A further example is provided by the assessment of extreme events impacts on forest productivity. This is particularly challenging due to the difficulty to identify the threshold effects on forest ecosystem resilience. Furthermore, hazard processes and their driving factors change over time. The current simulation approaches account for an increasing degree of complexity, but, in general, they oversimplify reality, especially when the analysis develops in the longer term. This is, for instance, an issue in forestry models where more research is needed to investigate how certain forest dynamics may change in response to long term changes in CO_2 fertilization. Similarly, the interaction of wildland fire with climate and vegetation has major effects on vegetation dynamics, ecosystem carbon budgets and patterns of biodiversity over longer timespans. The same applies to coupled hazard and adaptation models, which mostly lack the functionality to simulate changes over longer time periods, both historically and in future scenarios. The latter aspect is particularly important for addressing the effects from climate change in decision making and adaptation.

Human-physical interactions in hazard assessment: Research shows that human and physical systems are largely connected. Human activities influence physical processes, and vice versa. For instance, human impacts on the terrestrial hydrological cycle, or on many natural resources such as fisheries, are estimated to be much larger than those of climate change, especially when considering the local scale and the short-medium term (the next decade). Conversely, physical factors can influence human adaptive behaviour. For instance, after an extreme flood, risk perception is higher and can result in a higher uptake of adaptation measures. These interactions are largely missing in current hazard, vulnerability and adaptation models. The usual approach is to conduct a scenario-based analysis where hazard and vulnerability are calculated separately, and adaptation measures are assumed for a discrete point in time. Some advances in this direction can be observed, for instance, in the development of "socio-hydrology" and in the use of agent-based models (ABMs) which put the decision makers at the core of the adaptation analysis. Nonetheless, these coupled models, especially involving ABMs, require a huge amount of data that are often not available.

Macro-economics of impacts and adaptation assessment: Much work is still required regarding the development of models that assess the wider indirect economic impacts of climate change and adaptation. This includes, for instance, cascading network effects using empirical data instead of stylized or reduced-form approaches included in Integrated Assessment Models. Computable General Equilibrium models (CGEs) are used to partly address or overcome the criticism against reduced form climate change damage functions, but they lack the ability to capture discontinuity, irreversibility and non-market consequences typical of climate change impacts. Both typologies of model are then applied mostly to the study of mitigation and much less of adaptation. The main barrier is that macroeconomic assessments are developed at a level of aggregation which is larger than that of the majority of adaptation measures. This, coupled with the lack of reliable information on adaptation costs (see section 6.1 above), prevents a wider application of these approaches.

6.3 Gaps in model coupling

Coupling hazard, exposure and vulnerability with impact and adaptation assessments: Ideally, model-based analysis of adaptation should be conducted integrating the whole causal chain from climate stressors to adaptive responses into one unifying modelling framework. This is indeed the final aspirational goal of integrated assessment models. However, hard link integrated assessment models proposing this integration developing a unifying mathematical system are too coarse to support the implementation of adaptation measures. They can, at best, provide broad indications on trends and dynamics triggered by the implementation of adaptation strategies on other macroeconomic variables or policies. The alternative is to couple different models, managing each with a specific dimension of the chain with the desired level of detail. This "soft link" procedure is, however, burdensome under the computational point of view and requires a high level of multi-disciplinarity. As a consequence, it is not pursued to the extent needed. Examples where coupled models are required is in the energy sector, particularly for niche technologies such as wave and tidal power, but also on emerging ones such as solar power. The climate-water-energy-food nexus is another field of investigation where integrated assessment should be explored further. Studies coupling energy and water impacts at the basin level should be replicated and enriched systematically, as few studies review the whole of the EU. Furthermore, coupled impact modeling is also required for the tourism sector to assess issues such as snow reliability for skiing, the climate change impacts on biodiversity losses and forest fires on tourism. Many hazard models are still stand-alone models without having an impact module. There is also the need to foster a better coordination of adaptation and disaster risk reduction for a coherent response to climate and disaster risk (EC, 2018b). Opportunities for that are described in the EEA (2017). Additionally, links, synergies, combination and coherence of climate change adaptation and mitigation solutions at all levels and sectors should be further pursued, especially by climate-proofing sectors that are key for greenhouse gas emission reductions, such as land use, agriculture, energy or transport (EC, 2018a). Finally, more consideration should be given to the advantages provided by ecosystem-based adaptation, nature-based solutions and green infrastructures, whose multi-functional feature brings various environmental and social benefits (EC, 2018a).

6.4 Gaps in decision support

Gaps in decision support: Chapter 5 of the comprehensive desk review reports the main tools and techniques supporting the evaluation and prioritisation of adaptation options. This phase of the adaptation analysis, taking place "end of pipe", suffers from the shortcomings affecting the steps that precede in the adaptation investigation cycle. Eventually, no cost effectiveness, cost benefit or multicriteria analysis can be better than the input information processed. Under this respect, more information is definitely required on the cost of adaptation, especially in the long term.

A particularly challenging issue is subsequently the handling of uncertainty. Policy action on adaptation is not yet supported by fully transparent information on different uncertainty sources. This can prove to be particularly difficult though. Indeed, in addition to the uncertainty related to CCIV assessments, also that related to the effectiveness of adaptation options operates. Under situations of deep uncertainty or ambiguity that typically arise, choices based upon pure optimization criteria, such as CBA and CEA, may not correctly reflect the risks and tend to underestimate damages. Decision support should subsequently propose, in addition to these criteria, techniques applying robust decision making under uncertainty, such as Real Option Analysis, adaptation pathways and decision trees.

Another issue pertains to timing. CCIV and adaptation assessments are complex and require time and resources that may conflict with the needs and availability of decision making, especially at the more local level.

In principle, Decision Support Systems should support this. They are conceived as user friendly, user orientated guides to adaptation analyses to non-experts. In practice, the majority of DSSs do not evolve beyond the pilot demonstration phase and are hardly replicable outside its original context; it often offers a sectoral perspective on physical or environmental issues and does not examine the overall picture of multi-hazard risk. Most importantly, although developed for decision makers, it remains mostly confined to the research environment and is not perceived as user friendly for the broader public. This lack of diffusion and uptake depends on the complexity of adaptation decision. The more a DSS aspires to capture "real world" dynamics, the more it requires training and learning to be used. A common misunderstanding on DSS is that they are "simple" either in terms of data or learning effort requirements. In fact, they can facilitate the application of complex analyses and increase transparency, but they cannot eliminate complexities. At the same time, best practices in co-designing with the final users are not always followed, because they are costly in terms of time and resources. Consequently, often potential final users are not engaged frequently enough during the development of the DSS, they are not involved as co-developers and they are not assisted after the release of the DSS. This customization and post-delivery support are more typical of a commercial product than of a research output. Some of these problems are also common to climate services and have been extensively addressed by the H2020 projects EUMACS, CLARA and MARCO.

6.5 Gaps in Policy Support

The gap categories 6.1 to 6.4 highlight the research gaps from the literature reviewed in this comprehensive desk review, and predominately focus on informing decision and policy making. Yet, it is also noted that there is a distinct gap within the academic literature pertaining to the implementation of adaptation measures. Therefore, greater emphasis is also required to follow through research to include the final stages of climate adaptation strategies: in addition to conducting risk and impact assessments and decision support tools, research and guidance should also be developed to support decision makers with implementation and monitoring and evaluation stages of the policy cycle.

6.6 Summary

In summary:

- Many models still provide information with a spatial-temporal resolution which is not consistent (too coarse) with that of many adaptation actions. The shortcoming is particularly acute for the analysis and implementation of adaptation measures at the urban/ municipal level.
- There is still a divide between macro-economic assessment of impacts and adaptation and the local analysis. The empirical foundation of the former is still quite weak with the consequence of producing outputs that could be interpreted more qualitatively than quantitatively. The problem is progressively more severe, moving from the assessment of hazards, exposure, vulnerability and finally adaptation. More information is needed on adaptation costs and effectiveness. Similarly, the possibility to aggregate and transfer local adaption assessments to different contexts is limited.
- Notwithstanding improvements, models and assessments do not yet address satisfactorily feedbacks and interactions taking place within and between the different dimensions of the climate change adaptation process. The role played by multi hazard, cascading and compounding effects and interactions between physical and behavioural responses deserve more investigation to improve model coupling.
- There is not yet a common and consolidated practice in the communication of uncertainty. In particular, current assessments do not always enable to disentangle different uncertainty sources: that coming from the climate component, the social component and the models and the parameterization used.
- CCIV and adaptation assessment are complex and costly analyses that can exceed funding capacity of smaller administrations. Moreover, the time needed to release such analyses is often too long compared to that of decision making. This points to the need of methods facilitating, when possible "quick and operational" insights from adaptation modelling for policy assessment. Currently, many existing DSSs do not seem to offer a valid solution.

From the scrutiny of the desk review, it finally emerges that adaption options, their concrete implementation and evaluation were hardly ever the main object of the available modelling frameworks, and of the majority of available tools used to study adaptation, at the time such frameworks and tools were first designed. Their original purpose was usually to depict the status and evolution of some natural or economic systems under climatic change. Thus, most of the approaches identified and assessed in the present study cover extensively the first two steps of the adaptation analysis of 'preparing the ground for adaptation' and 'assessing risk and vulnerability to climate change'. A much more limited number of studies relate to the steps 'identifying adaptation options', 'assessing adaptation options', and 'implementing adaptation strategies', with very limited research also including 'implementation' and 'monitoring and evaluation strategies'.

References

ABEDINPOUR, A., SARANGI, A RAJPUT TBS AND SINGH M (2014) Prediction of maize yield under future water availability scenarios using the AquaCrop model. CLIMATE CHANGE AND AGRICULTURE RESEARCH PAPER. Journal of Agricultural Science 152, 558–574. ©

Abar, S., Theodoropoulos, G. K., Lemarinier, P. and O'Hare, G. M. P.: Agent-based Modelling and Simulation tools: A review of the state-of-art software, Comput. Sci. Rev., 24, 13–33, doi:10.1016/j.cosrev.2017.03.001, 2017.

Abson, D.J., Dougill, A.J. and Stringer, L.C. 2012. Using Principal Component Analysis for information-rich socio-ecological vulnerability mapping in Southern Africa. Applied Geography.

Adger, W. *et al.* (2004) 'New indicators of vulnerability and adaptive capacity', Tyndall Centre for Climate Change Research, 122. Available at: https://pdfs.semanticscholar.org/6ff4/2b2e526e40f7d1a82db8cfa8057b4ca7355c.pdf (Accessed: 27 November 2016).

Aerts, J.C.J.H., Botzen, W.J.W. (2011). Climate change impacts on pricing long-term flood insurance: A comprehensive study for the Netherlands. Global Environmental Change, 21: 1045-1060.

Agrawala, S., Bosello, F., Carraro, C., De Cian, E., and Lanzi, E. (2011). "Adapting to Climate Change: Costs, Benefits, and Modeling Approaches", International Review of Environmental and Resource Economics 5, pp. 245–284.

Agrawala, S., Bosello, F., Carraro, C., De Cian, E., Lanzi, E., de Bruin, K., and Dellink, R. (2010). "PLAN or REACT? Analysis of Adaptation Costs and Benefits Using Integrated Assessment Models". OECD Environment Working Papers, No. 23, OECD Publishing.

Aguejdad, R., Hidalgo, J., Doukari, O., & Masson, V. (2012). Assessing the influence of long-term urban growth scenarios on urban climate. (2010).

Aguiar, A., Chepeliev, M., Corong, E., McDougall, R., & van der Mensbrugghe, D. (2019), "The GTAP Data Base: Version 10", Journal of Global Economic Analysis, 4(1), 1-27.

Aguilera, P. A., Fernández, A., Fernández, R., Rumí, R., & Salmerón, A. (2011). Bayesian networks in environmental modelling. Environmental Modelling & Software, 26(12), 1376–1388.

Alcasena, F.J., Ager, A.A., Bailey, J.D., Pineda, N., Vega-García, C. (2019). Towards a comprehensive wildfire management strategy for Mediterranean areas: Framework development and implementation in Catalonia, Spain. Journal of Environmental Management, 231, 303-320. https://doi.org/10.1016/j.jenvman.2018.10.027

Alewell, C., Borrelli, P., Meusburger, K., & Panagos, K. (2019). Using the USLE: Chances, challenges and limitations of soil erosion modelling. International Soil and Water Conservation Research, 7(3), 203-225

Alfieri, L. *et al.* (2016) 'Modelling the socio-economic impact of river floods in Europe', Natural Hazards and Earth System Sciences, 16(6), pp. 1401–1411. doi: 10.5194/nhess-16-1401-2016.

Alfieri, L., Salamon, P., Bianchi, A., Neal, J., Bates, P. and Feyen, L., 2014. Advances in pan-European flood hazard mapping. Hydrological processes, 28(13), pp.4067-4077.

Alistair Hunt, Julia Ferguson, Michela Baccini, Paul Watkiss, Vladimir Kendrovski (2016). Climate and Weather Service Provision: Economic Appraisal of Adaptation to Health Impacts. Climate Services. DOI: 10.1016/j.cliser.2016.10.004

Alkemade, R., Van Oorschot, M., Miles, L., Nellemann, C., Bakkenes, M., & Ten Brink, B. (2009). GLOBIO3: A framework to investigate options for reducing global terrestrial biodiversity loss. Ecosystems, 12(3), 374–390. https://doi.org/10.1007/s10021-009-9229-5

Amadio, M., Scorzini, A.R., Carisi, F., Essenfelder, A.H., Domeneghetti, A., Mysiak, J. and Castellarin, A., 2019. Testing empirical and synthetic flood damage models: the case of Italy. Natural Hazards and Earth System Sciences, 19(3), pp.661-678.

Anderegg, W. R., T. Klein, M. Bartlett, L. Sack, A. F. Pellegrini, B. Choat, and S. Jansen, 2016: Meta-analysis reveals that hydraulic traits explain cross-species patterns of drought-induced tree mortality across the globe. Proc. Natl. Acad. Sci. USA, 113, 5024–5029, https://doi.org/10.1073/pnas.1525678113.

Andrés, B.O., Miren, D.R., & Gregorio, M. (2004). Site index curves and growth model for Mediterranean maritime pine (Pinus pinaster Ait.) in Spain. For. Ecol. Manag., 201, 187–197.

Andrews, P.L. (2014). Current status and future needs of the BehavePlus Fire Modeling System. International Journal of Wildland Fire, 23, 21-33. https://doi.org/10.1071/WF12167

Andrews, P.L., Loftsgaarden, D.O., Bradshaw, L.S. (2003). Evaluation of fire danger rating indexes using logistic regression and percentile analysis. International Journal of Wildland Fire, 12(2), 213-226. https://doi.org/10.1071/WF02059

Anna, S., Nadejda, K., & Arnaud, M. (2017). Mainstreaming multi-risk approaches into policy. Geosciences (Switzerland), 7(4), 1–18. https://doi.org/10.3390/geosciences7040129

Anthoff, D., and Tol, R.S.J. (2014)."Climate policy under fat-tailed risk: An application of FUND", Annals of Operations Research, 220(1), 223–237

Anthoff, D., Hepburn, C., and Tol, R. S. J. (2009), "Equity weighting and the marginal damage costs of climate change", Ecological Economics, 68(3), 836–849.

Anthoff, D., Tol, R. S. J., & Yohe, G. W. (2009), "Discounting for Climate Change", Economics: The Open-Access, Open-Assessment E-Journal, 3(2009–24).

Antle, J. M., Basso, B., Conant, R. T., Godfray, H. C. J., Jones, J. W., Herrero, M., Howitt, R.E., Keating, B.A., Munoz-Carpena, R., Rosenzweig, C., Tittonell, P., Wheeler, T. R. (2017). Towards a new generation of agricultural system data, models and knowledge products: Design and improvement. Agricultural Systems, 155, 255–268. https://doi.org/10.1016/j.agsy.2016.10.002

Arca, B., Bacciu, V., Duce, P., Pellizzaro, G., Salis, M., Spano, D. (2007a). Use of FARSITE simulator to produce fire probability maps in a Mediterranean area. In T.J., Brown, B.E., Potter, N.K., Larkin, K.R., Anderson (Eds.). Proceedings of the 7th Symposyum on Fire and Forest Meteorology (23–26 October 2007, Bar Harbor, ME). American Meteorological Society: Boston, MA. Retrieved from http://ams.confex.com/ams/7firenortheast/techprogram/paper_127440.htm

Arca, B., Duce, P., Laconi, M., Pellizzaro, G., Salis, M., Spano, D. (2007b). Evaluation of FARSITE simulator in Mediterranean maquis. International Journal of Wildland Fire, 16, 563–572. https://doi.org/10.1071/WF06070

Arderne, C., Zorn, C., Nicolas, C., Koks E.E., 2020. Predictive mapping of the global power system using open data. Scientific Data 7, 19

Armington, P. S. (1969): "A Theory of Demand for Products Distinguished by Place of Production," International Monetary Fund Staff Papers, 16, 159–178.

Arnold, J. G., Kiniry, J. R., Srinivasan, R., Williams, J. R., Haney, E. B., & Neitsch, S. L. (2012). Soil & Water Assessment Tool: Input/Output Documentation. Version 2012. In Texas Water Resources Institute. College Station, TX, USA.

Arnold, J. G., Srinivasan, R., Muttiah, R. S., & Williams, J. R. (1998). Large Area Hydrologic Modeling and Assessment Part I: Model Development. Journal of the American Water Resources Association, 34(1), 73–89. https://doi.org/10.1111/j.1752-1688.1998.tb05962.x

Arora, V.K. & Boer, G.J. (2005). Fire as an interactive component of dynamic vegetation models. Journal of Geophysical Research, 110, G02008. https://doi.org/10.1029/2005JG000042

ASC (2011). Research to identify potential low-regrets adaptation options to climate change in the residential buildings sector. Commissioned by the Adaptation Sub Committee, July 2011.

Asseng, S., Martre, P., Maiorano, A., Rötter, R. P., O'Leary, G. J., Fitzgerald, G. J., … Ewert, F. (2019). Climate change impact and adaptation for wheat protein. Global Change Biology, 25(1), 155–173. https://doi.org/10.1111/gcb.14481

Asseng, S., Zhu, Y., Wang, E., & Zhang, W. (2015). Crop modeling for climate change impact and adaptation. In Crop Physiology (pp. 505–546). Elsevier. https://doi.org/10.1016/B978-0-12-417104-6.00020-0

Auffhammer, M. (2018), Quantifying Economic Damages from Climate Change, The Journal of Economic Perspectives,32(4), 33-52

Aven, T. 2011. On some recent definitions and analysis frameworks for risk, vulnerability, and resilience. Risk Analysis 31(4): 515–522.

Ayllón, D., S. F. Railsback, B. C. Harvey, I. García Quirós, G. G. Nicola, B. Elvira, and A. Almodóvar. 2019. Mechanistic simulations predict that thermal and hydrological effects of climate change on Mediterranean trout cannot be offset by adaptive behaviour, evolution, and increased food production. Science of the Total Environment 693:133648.

Baccini, M., Biggeri, A., Accetta, G., Kosatsky, T., Katsouyanni, K., Analitis, A., and P. Michelozzi (2008). Heat effects on mortality in 15 European cities. Epidemiology, 19(5), 711-719.

Bach S, Kohlhaas M, Meyer B, Praetorius B, Welsch H. (2002), "The effects of environmental fiscal reform in Germany: a simulation study", Energy Policy, 30:803–811.

Bachmair S, Svensson C, Prosdocimi I, Hannaford J and Stahl K (2017) Developing drought impact functions for drought risk management. Natural Hazards and Earth System Sciences vol 17, 1947-1960

Bader, B., Yan, J. & Zhang, X. Automated selection of r for the r largest order statistics approach with adjustment for sequential testing. Stat Comput 27, 1435–1451 (2017). https://doi.org/10.1007/s11222-016-9697-3

Badjeck, M. C., E. H. Allison, A. S. Halls, and N. K. Dulvy. 2010. Impacts of climate variability and change on fishery-based livelihoods. Marine Policy 34:375–383.

Bagnold, R.A. (1941). The Physics of Blown Sand and Desert Dunes. London: Methuen & Co. ed..

Bahn, O., M. Chesney, and J. Gheyssens. 2010. "The Effect of Adaptation Measures on the Adoption of Clean Technologies." Paper presented at the WCERE Congress, Montreal, 2010.

Bailey, R. L., & Ware, K. D. (1983). Compatible basal-area growth and yield model for thinned and unthinned stands. Can. J. For. Res., 13, 563–571.

Bakkenes, M., Alkemade, J. R. M., Ihle, F., Leemans, R., & Latour, J. B. (2002). Assessing effects of forecasted climate change on the diversity and distribution of European higher plants for 2050. Global Change Biology, 8(4), 390–407. https://doi.org/10.1046/j.1354-1013.2001.00467.x

Bakkensen, L. A. *et al.* (2017) 'Validating Resilience and Vulnerability Indices in the Context of Natural Disasters', Risk Analysis. Wiley/Blackwell (10.1111), 37(5), pp. 982–1004. doi: 10.1111/risa.12677.

Ban, N., Schmidli, J., & Schär, C. (2015). Heavy precipitation in a changing climate: Does short-term summer precipitation increase faster?. Geophysical Research Letters, 42(4), 1165-1172.

Barker, T., De-Ramon, S. and Pollitt, H.(2009),"Revenue Recycling and Labour Markets: Effects on Costs of Policies for Sustainability", In V. Bosetti, R. Gerlagh and S. Schleicher (Eds.) Modeling Transitions to Sustainable Development, Cheltenham: Edward Elgar.

Barnett, D. N., Brown, S. J., Murphy, J. M., Sexton, D. M. H. and Webb, M. J. (2006). Quantifying uncertainty in changes in extreme event frequency in response to doubled CO2 using a large ensemble of GCM simulations. Climate Dynamic, 26, doi:10.1007/s00382-005-0097-1

Bartelink, H.H., & Mohren, G.M.J. (2004). Modelling at the interface between scientific knowledge and management issues. Towards the sustainable use of Europe's forests. Forest Ecosystem and Landscape Research: Scientific Challenges and Opportunities, 49, 21-30.

Bartzokas, A., Kotroni, V., Lagouvardos, K., Lolis, C. J., Gkikas, A., and Tsirogianni, M. I. (2010). Weather forecast in northwestern Greece: RISKMED warnings and verification of MM5 model, Natural Hazards and Earth System Science,10, 383–394

Baruffi, F., Cisotto, A., Cimolino, A., Ferri, M., Monego, M., Norbiato, D., … Marcomini, A. (2012). Climate change impact assessment on Veneto and Friuli Plain groundwater. Part I: an integrated modeling approach for hazard scenario construction. The Science of the Total Environment, 440, 154–166. https://doi.org/10.1016/j.scitotenv.2012.07.070

Basso, B., Cammarano, D., & Carfagna, E. (2013). Review of crop yield forecasting methods and early warning systems. Proceedings of the First Meeting of the Scientific Advisory Committee of the Global Strategy to Improve Agricultural and Rural Statistics. FAO, Rome (2013). Retrieved from: http://www.fao.org/fileadmin/templates/ess/documents/meetings_and_workshops/GS_SAC_2013/Improving_methods_for_crops_estimates/Crop_Yield_Forecasting_Methods_and_Early_Warning_Systems_Lit_review.pdf [16 December 2019].

Basso, B., Ritchie, J. T., Grace, P. R., & Sartori, L. (2006). Simulation of Tillage Systems Impact on Soil Biophysical Properties Using the SALUS Model. Italian Journal of Agronomy, 1(4), 677. https://doi.org/10.4081/ija.2006.677

Bassu, S., Brisson, N., Durand, J.-L., Boote, K., Lizaso, J., Jones, J. W., … Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors? Global Change Biology, 20(7), 2301–2320. https://doi.org/10.1111/gcb.12520

Bates, P., Trigg, M., Neal, J., & Dabrowa, A. (2013). LISFLOOD-FP: User manual. School of Geographical Sciences, Univeristy of Bristol, pp. 1–49. Bristol, UK: University of Bristol.

Battista e Silva, F., Forzieri, G., Herrera, M.A.M., Bianchi, A., Lavalle, C. and Feyen, L., 2019. HARCI-EU, a harmonized gridded dataset of critical infrastructures in Europe for large-scale risk assessments. Scientific data, 6(1), pp.1-11.

Bauer, N., Hilaire, J., Brecha, R. J., Edmonds, J., Jiang, K., Kriegler, E., ... & Sferra, F. (2016). Assessing global fossil fuel availability in a scenario framework. Energy, 111, 580-592.

Bayissa, Yared; Maskey, Shreedhar; Tadesse, Tsegaye; Andel, Schalk Jan van; Moges, Semu; Griensven, Ann van; and Solomatine, Dimitri, "Comparison of the Performance of Six Drought Indices in Characterizing Historical Drought for the Upper Blue Nile Basin, Ethiopia" (2018). Drought Mitigation Center Faculty Publications. 137.

Bedia, J., Herrera, S., Camia, A., Moreno, J.M., Gutierrez, J.M. (2014). Forest fire danger projections in the Mediterranean using ENSEMBLES regional climate change scenarios. Climate Change, 122, 185–199. http://dx.doi.org/10. 1007/s10584-013-1005-z

Belgiu, M., & Drăgu, L. (2016). Random forest in remote sensing: A review of applications and future directions. ISPRS Journal of Photogrammetry and Remote Sensing, 114, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W., & Courchamp, F. (2012). Impacts of climate change on the future of biodiversity. Ecology Letters, 15(4), 365–377. https://doi.org/10.1111/j.1461-0248.2011.01736.x

Beniston, M. (2003). Climatic change in mountain regions: a review of possible impacts. In Climate variability and change in high elevation regions: Past, present & future (pp. 5-31). Springer, Dordrecht.

Bergez, J. E., Raynal, H., Launay, M., Beaudoin, N., Casellas, E., Caubel, J., … Ruget, F. (2014). Evolution of the STICS crop model to tackle new environmental issues: New formalisms and integration in the modelling and simulation platform RECORD. Environmental Modelling & Software, 62, 370–384. https://doi.org/10.1016/j.envsoft.2014.07.010

Berrittella, M., Bigano, A., Roson, R. and Tol, R. S. J.: A general equilibrium analysis of climate change impacts on tourism, Tour. Manag., 27(5), 913–924, doi:10.1016/j.tourman.2005.05.002, 2006.

Bertram C, Luderer G, Popp A, Minx JC, Lamb WF, Miodrag Stevanović, Humpenöder F, Giannousakis A, Kriegler E (2018), "Targeted policies can compensate most of the increased sustainability risks in 1.5 °C mitigation scenarios", Environmental Research Letters, 13:064038.

Bharwani, S., Downing, T.E., Varela-Ortega, C., Blanco, I., Esteve, P., Carmona, G., Taylor, R., Devisscher, T., Coll Besa, M., Tainio, A., Ballard, D. and Watkiss, P. 2013. Social Network Analysis: Decision Support Methods for Adaptation, MEDIATION Project, Briefing Note 8.

Bhave, A. G., Conway, D., Dessai, S., & Stainforth, D. A. J. C. R. M. (2016). Barriers and opportunities for robust decision making approaches to support climate change adaptation in the developing world. 14, 1-10.

Bierkens, M. F. P. (2015). Global hydrology 2015: State, trends, and directions. Water Resources Research, 51, 4923–4947. https://doi.org/10.1002/2015WR017173.

Bigano, A., Bosello, F., Roson, R., & Tol, R. S. J. (2008). Economy-wide impacts of climate change: A joint analysis for sea level rise and tourism. Mitigation and Adaptation Strategies for Global Change, 13(8). https://doi.org/10.1007/s11027-007-9139-9

Bindi, M., Palosuo, T., Trnka, M., & Semenov, M. (2015). Modelling climate change impacts on crop production for food security. Climate Research, 65, 3–5. https://doi.org/10.3354/cr01342

Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., … Welle, T. (2013). Framing vulnerability, risk and societal responses: the MOVE framework. Natural Hazards, 67(2), 193–211. https://doi.org/10.1007/s11069-013-0558-5

Bloemendaal, N., de Moel, H., Muis, S., Haigh, I.D., & Aerts, J.C.J.H. Estimation of global tropical cyclone wind speed probabilities using the STORM dataset, Sci. Data. (in review)

Böhringer, C., Fisher, C., and Rosendahl, K. E. (2010). "The Global Effects of Subglobal Climate Policies", Resources for the Future Discussion Paper, pp. 10–48.

Böhringer, C., Rutherford, T., and Tol, R. (2009). "The EU 20/20/20 Targets: An Overview of the EMF22 Assessment", Energy Economics, 31, 268–273.

Boltz, F., LeRoy Poff, N., Folke, C., Kete, N., Brown, C. M., St. George Freeman, S., Matthews, J. H., Martinez, A., & Rockström, J. (2019). Water is a master variable: Solving for resilience in the modern era. Water Security, 8, 100048. https://doi.org/https://doi.org/10.1016/j.wasec.2019.100048

Bonazzi, A., Cusack, S., Mitas, C., & Jewson, S. (2012). The spatial structure of European wind storms as characterized by bivariate extreme-value Copulas. Natural Hazards & Earth System Sciences, 12(5).

Bonzanigo, L., Brown, C., Harou, J., Hurford, A., Karki, P., Newmann, J., Ray, P. ,2015:. "South Asia investment decision making in hydropower: Decision tree case study of the Upper Arun Hydropower Project and Koshi Basin Hydropower Development in Nepal." GEEDR South Asia, The World Bank. Report No.: AUS 11077

Boote, K. J., Porter, C., Jones, J. W., Thorburn, P. J., Kersebaum, K. C., Hoogenboom, G., … Fleisher, D. (2016). Sentinel Site Data for Crop Model Improvement—Definition and Characterization. Advances in Agricultural Systems Modeling. doi:10.2134/advagricsystmodel7.2014.0019

Borsuk, M. E., Stow, C. A., & Reckhow, K. H. (2004). A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecological Modelling, 173(2), 219–239.

Bosello, F. and C. Carraro (2001)."Recycling Energy Taxes: Impacts on a Disaggregated Labour Market", Energy Economics, 23(5): 569-594.

Bosello, F., Buchner, B., and Carraro, C. (2003). "Equity, Development and Climate Change Control", Journal of the European Economic Association, Vol. 1.

Bosello, F., Carraro C. and E. De Cian (2010), 'Climate policy and the optimal balance between mitigation, adaptation and unavoided damage', Climate Change Economics, 1(2), 71-92.

Bosello, F., Carraro C. and E. De Cian (2013). "Adaptation can help mitigation: an integrated approach to post 2012 climate policy", Environment and Development Economics, 18, pp 270-290

Bosello, F., Nicholls, R. J., Richards, J., Roson, R. and Tol, R. S. J.: Economic impacts of climate change in Europe: sea-level rise, Clim. Change, 112(1), 63–81, doi:10.1007/s10584-011-0340-1, 2012.

Bosello, F., Roson, R. and Tol, R. S. J.: Economy-wide estimates of the implications of climate change: sea level rise, Environ. Resour. Econ., 37(3), 549–571, doi:10.1007/s10640-006-9048-5, 2007.

Bosetti V, Marangoni G, Borgonovo E, Diaz Anadon L, Barron R, McJeon H, Politis S, Friley P (2015), “Sensitivity to energy technology costs: a multi-model comparison analysis”, Energy Policy. https ://doi. org/10.1016/j.enpol .2014.12.012

Bosetti, V., Carraro, C., De Cian, E., Massetti, E., and Tavoni, M. (2011). “Incentives and Stability of Environmental Coalitions: An Integrated Assessment”, FEEM Note di Lavoro, 97.2011.

Botzen, W.J.W., Bouwer, L.M. (2016). Weather indicators for insured hailstorm damage to motor vehicles and potential climate change impacts. Geneva Papers on Risk and Insurance, 41(3): 512-527.

Botzen, W.J.W., Kunreuther, H., Michel-Kerjan, E. (2015). Divergence between individual perceptions and objective indicators of tail risks: Evidence from floodplain residents in New York City. Judgment and Decision Making, 10(4): 365-85.

Botzen, W.J.W., van den Bergh, J.C.J.M. (2012). Risk attitudes to low-probability climate change risks: WTP for flood insurance. Journal of Economic Behavior and Organization, 82(1): 151-166.

Boughton, D., Smith, E. and O’Neill, R. 1999. Regional vulnerability: a conceptual framework. Ecosyst. Health. 5, pp.312–322.

Bouwer, L., Capriolo, A., Chiabai, A., Foudi, S., Garrote, L., Harmackova, Z. V., … Zandersen, M. (2018). Upscaling the impacts of climate change in different sectors and adaptation strategies. In H. Sanderson, M. Hilden, D. Russel, G. Penha-Lopes, & A. Capriolo (Eds.), Adapting to climate change in Europe (pp. 173–244). Amsterdam: Elsevier.

Bowen, K.J., Alexander, D., Miller, F. and Dany, V. 2014. Using social network analysis to evaluate health-related adaptation decision-making in Cambodia. International journal of environmental research and public health. 11(2), pp.1605–25.

Boyd, R Wade, S. and Walton, H (2006) in Metroeconomica et al (2006). Climate Change Impacts and Adaptation: Cross-Regional Research Programme Project E. Final report to Defra, London, UK.

Brandt, L.A., Butler, P.R., Handler, S.D., Janowiak, M.K., Shannon, P.D. and Swanston, C.W. 2017. Integrating Science and Management to Assess Forest Ecosystem Vulnerability to Climate Change. Journal of Forestry. 115(May), pp.212–221.

Braun, S., Thomas, V.F.D., Quiring, R., & Fluckiger, W. (2010). Does nitrogen deposition increase forest production? The role of phosphorus. Environmental Pollution, 158(6), 2043-2052.

Bregaglio, S., Giustarini, L., Suarez, E., Mongiano, G., & De Gregorio, T. (2020). Analysing the behaviour of a hazelnut simulation model across growing environments via sensitivity analysis and automatic calibration. Agricultural Systems, 181, 102794. doi:10.1016/j.agsy.2020.102794

Brisson, N., Gary, C., Justes, E., Roche, R., Mary, B., Ripoche, D., … Sinoquet, H. (2003). An overview of the crop model STICS. European Journal of Agronomy, 18(3–4), 309–332. https://doi.org/10.1016/S1161-0301(02)00110-7

Brown, C., Ghile, Y., Laverty, M., & Li, K. J. W. R. R. (2012). Decision scaling: Linking bottom-up vulnerability analysis with climate projections in the water sector. 48(9).

Browning, K.A. (2004), The sting at the end of the tail: Damaging winds associated with extratropical cyclones. Q.J.R. Meteorol. Soc., 130: 375-399. doi:10.1256/qj.02.143

Brugha, R. and Varvasovszky, Z. 2000. Stakeholder analysis: a review. Health Policy and Planning. 15(3), pp.239–246.

Bubeck, P., Botzen, W.J.W., Aerts, J.C.J.H. (2012). A review of risk perceptions and other factors that influence flood mitigation behavior. Risk Analysis, 32(9): 1481-1495.

Bubeck, P., Dillenardt, L., Alfieri, L., Feyen, L., Thieken, A. H., & Kellermann, P. (2019). Global warming to increase flood risk on European railways. Climatic Change, 1-18.

Buchholz, T., Friedland, A.J., Hornig, C.E., Keeton, W.S., Zanchi G., & Nunery J (2014). Mineral soil carbon fluxes in forests and implications for carbon balance assessments. GCB Bioenergy, 6(4),305–311.

Bugmann, H., & Bigler, C. (2010). Succession modeling shows that CO2 fertilization effect in forests is offset by reduced tree longevity. Oecologia, 165(2), 533-544.

Bullock, P. (2004). Climate Change Impacts. In: Encyclopedia of Soils in the Environment (Ed: Daniel Hillel). Elsevier: Amsterdam.

C3S, C. C. C. S. (2016). Service for Water Indicators in Climate Change Adaptation - SWICCA. Retrieved June 6, 2017, from SWICCA website: http://swicca.climate.copernicus.eu/

Calliari, E., Michetti, M., Farnia, L. and Ramieri, E. 2019. A network approach for moving from planning to implementation in climate change adaptation: Evidence from southern Mexico. Environmental Science and Policy. 93, pp.146–157.

Campbell, E.E., & Paustian, K. (2015). Current developments in soil organic matter modeling and the expansion of model applications: a review. Environment Research Letter, 10, 123004.

Caires, S. A Comparative Simulation Study of the Annual Maxima and the Peaks-Over-Threshold Methods. J. Offshore Mech. Arct. Eng. 138, (2016).

Cardona, O. D., Van Aalst, M. K., Birkmann, J., Fordham, M., Mc Gregor, G., Rosa, P., ... & Keim, M. (2012). Determinants of risk: exposure and vulnerability. In Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change (pp. 65-108). Cambridge University Press.

Cardone, V.J., Cox, A.T. Tropical cyclone wind field forcing for surge models: critical issues and sensitivities. Nat Hazards 51, 29–47 (2009). https://doi.org/10.1007/s11069-009-9369-0

Carrao H and Barbosa P (2015) Models of Drought Hazard, Exposure, Vulnerability and Risk for Latin America. Technical Report from the European Commission – Joint

Research Centre (EC-JRC) and Institute for Environment and Sustainability (IES) EUROCLIMA II - Desertification, Land Degradation and Drought (DLDD), and bio-physical modeling for crop yield estimation in Latin America under a changing climate.

Carrão, H., Naumann, G. and Barbosa, P. (2018) 'Global projections of drought hazard in a warming climate: a prime for disaster risk management', Climate Dynamics. Springer Berlin Heidelberg, 50(5–6), pp. 2137–2155. doi: 10.1007/s00382-017-3740-8.

Cassou, C., Terray, L., & Phillips, A. S. (2005). Tropical Atlantic influence on European heat waves. Journal of climate, 18(15), 2805-2811.

Castruccio, S., & Genton, M. G. (2018). Principles for statistical inference on big spatio-temporal data from climate models. Statistics & Probability Letters, 136, 92–96. https://doi.org/10.1016/J.SPL.2018.02.026

Chalise, S. and Naranpanawa, A.: Climate change adaptation in agriculture: A computable general equilibrium analysis of land-use change in Nepal, Land use policy, 59, 241–250, doi:10.1016/J.LANDUSEPOL.2016.09.007, 2016

Challinor, A. J., Müller, C., Asseng, S., Deva, C., Nicklin, K. J., Wallach, D., Vanuytrecht, E., Whitfield, S., Ramirez-Villegas, J., Koehler, A.-K. (2018). Improving the use of crop models for risk assessment and climate change adaptation. Agricultural Systems, 159, 296–306. https://doi.org/10.1016/j.agsy.2017.07.010

Chan, K. M. A., Shaw, M. R., Cameron, D. R., Underwood, E. C., & Daily, G. C. (2006). Conservation planning for ecosystem services. PLoS Biology, 4(11), 2138–2152. https://doi.org/10.1371/journal.pbio.0040379

Chang, S.-H., Chiang, K.T. (2011). The potential impact of climate change on typhoontriggered landslides in Taiwan, 2010–2099. Geomorphology 133, 143–151.

Chaudhry, S. J., Hand, M., Kunreuther, H. (2018). Extending the time horizon: Elevating concern for rare events by communicating losses over a longer period of time. Working Paper University of Pennsylvania.

Chen, F., Kusaka, H., Bornstein, R., Ching, J., Grimmond, C. S. B., Grossman-Clarke, S., … Zhang, C. (2011). The integrated WRF/urban modelling system: Development, evaluation, and applications to urban environmental problems. International Journal of Climatology, 31(2), 273–288. https://doi.org/10.1002/joc.2158

Chen, M., Shi, W., Xie, P., Silva, V. B., Kousky, V. E., Wayne Higgins, R., & Janowiak, J. E. (2008). Assessing objective techniques for gauge-based analyses of global daily precipitation. Journal of Geophysical Research: Atmospheres, 113(D4).

Chevalier, J.M. and Buckles, D.J. 2008. SAS2. A guide to collaborative inquiry and social engagement. SAGE Publications.

Chiabai, A., Spadaro, J.V., Neumann, M.B., 2018. Valuing deaths or years of life lost? Economic benefits of avoided mortality from early heat warning systems. Mitigation and Adaptation Strategies for Global Change. https://doi.org/10.1007/s11027-017-9778-4

Christensen J H, Hewitson B, Busuioc A, Chen A, Gao X, Held I, Jones R, Kolli R K, Kwon W-T, Laprise R, Magaña Rueda V, Mearns L, Menéndez C G, Räisänen J, Rinke A, Sarr A and Whetton P. (2007). Regional Climate Projections. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon S, Qin D, Manning M, Chen Z, Marquis M, Averyt K B, Tignor M and Miller H L (eds)]. Cambridge University Press. Cambridge, United Kingdom and New York, NY, USA

Christensen, V., and C. J. Walters. 2004. Ecopath with Ecosim: Methods, capabilities and limitations. Ecological Modelling 172:109–139.

Christidis, N., & Stott, P.A. (2016). Attribution analyses of temperature extremes using a set of 16 indices. Weather and Climate Extremes, 14, 24-35

Ciabatta, L., Camici, S., Brocca, L., Ponziani, F., Stelluti, M., Berni, N., & Moramarco, T. J. J. O. H. (2016). Assessing the impact of climate-change scenarios on landslide occurrence in Umbria Region, Italy. Journal of Hydrology, 541, 285-295.

Ciscar JC, Feyen L, Soria A, Lavalle C, Raes F, Perry M, Nemry F, Demirel H, Rozsai M, Dosio A, Donatelli M, Srivastava A, Fumagalli D, Niemeyer S, Shrestha S, Ciaian P, Himics M, Van Doorslaer B, Barrios S, Ibáñez N, Forzieri G, Rojas R, Bianchi A, Dowling P, Camia A, Libertà G, San Miguel J, de Rigo D, Caudullo G, Barredo JI, Paci D, Pycroft J, Saveyn B, Van Regemorter D, Revesz T, Vandyck T, Vrontisi Z, Baranzelli C, Vandecasteele I, Batista e Silva F, Ibarreta D (2014). Climate Impacts in Europe. The JRC PESETA II Project. JRC Scientific and Policy Reports, EUR 26586EN.

Ciscar, J.C., D. Ibarreta, A. Soria, A. Dosio, A.Toreti, A. Ceglar, D. Fumagalli, F. Dentener, R. Lecerf, A. Zucchini, L. Panarello, S. Niemeyer, I. Pérez-Domínguez, T. Fellmann, A. Kitous, J. Després, A. Christodoulou, H. Demirel, L. Alfieri, F. Dottori, M.I. Vousdoukas, L. Mentaschi, E. Voukouvalas, C. Cammalleri, P. Barbosa, F. Micale, J.V. Vogt, J.I. Barredo, G. Caudullo, A. Mauri, D. de Rigo, G. Libertà, T. Houston Durrant, T. Artés Vivancos, J. San-Miguel-Ayanz, S.N. Gosling, J. Zaherpour, A. De Roo, B. Bisselink, J. Bernhard, L., Bianchi, M. Rozsai, W. Szewczyk, I. Mongelli and L. Feyen, (2018). Climate impacts in Europe: Final report of the JRC PESETA III project, EUR 29427 EN, Publications Office of the European Union, Luxembourg,. ISBN 978-92-79-97218-8, doi:10.2760/93257, JRC112769.

Climate-ADAPT. (2020). Adaptation Support Tool. https://climate-adapt.eea.europa.eu/knowledge/tools/adaptation-support-tool

Coastal Hazard Wheel. (2020, January 22). Coastal Hazard Wheel - Open Access platform. Retrieved from Coastal Hazard Wheel: https://www.coastalhazardwheel.org/
Cochrane, K., D. Soto, and T. Bahri. 2009. Climate change implications for fisheries and aquaculture Overview of current scientific knowledge FOOD AND AGRICULTURE ORGANIZATION OF THE UNITED NATIONS.

Coles, S., 2001: An Introduction to the Statistical Modelling of Extreme Values. Springer Texts in Statistics, SpringerVerlag: London.

Coles, S., Bawa, J., Trenner, L., & Dorazio, P. (2001). An introduction to statistical modeling of extreme values (Vol. 208, p. 208). London: Springer.

Collingham, Y. C., Hill, M. O., & Huntley, B. (1996). The migration of sessile organisms: a simulation model with measurable parameters. Journal of Vegetation Science, 7(6), 831–846. https://doi.org/10.2307/3236461

Comegna, L., Picarelli, L., Bucchignani, E., Mercogliano, P., (2013). Potential effects of incoming climate changes on the behaviour of slow active landslides in clay. Landslides 10(4), 373–391.

Congalton, R.G., Green, K. (1999). Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. Boca Raton, FL: Lewis Publishers

Connor, L., S. Shephard, K. Rocks, and F. L. Kelly. 2019. Potential climate change impacts on Arctic char Salvelinus alpinus L. in Ireland. Fisheries Management and Ecology 26:527–539.

Cooper JAG, Pilkey OH (2004) Sea level rise and shoreline retreat: time to abandon the Bruun rule. Glob Planet Change 43:157

Corinna, C., & Vladimir, V. (1995). Support-Vector Networks. Machine Learning, 20(3), 273–297. https://doi.org/10.1007/BF00994018

Cousins, S. H. (1997). Species Diversity Measurement: Choosing the Right Index. In TREE (Vol. 6).

Crausbay S, Ramirz A (2017) Defining Ecological drought for the twenty-first century. BAMS December 2017

CRI. (2016a). Research Report Vol 4 - Measuring City Resilience. Rockefeller Foundation and ARUP.

CRI. (2016b). Research Report Vol 6 - Measurement Guide. Rockefeller Foundation and ARUP.

Cushman, S.A., McKenzie, D., Peterson, D.L., Littell, J., McKelvey, K. (2007). Research agenda for integrated landscape modeling. Rocky Mountain Research Station, RMRS-GTR-194. Fort Collins, CO: USDA Forest Service

Cutter, S. L., Boruff, B. J. and Shirley, W. L. (2003) 'Social Vulnerability to Environmental Hazards', Social Science Quarterly, 84(2), pp. 242–261. doi: 10.1111/1540-6237.8402002.

Cutter, S.L., Emrich, C. T., Morath, D. P., & Dunning, C. M. (2013). Integrating social vulnerability into federal flood risk management planning. Journal of Flood Risk Management, 6(4), 332–344. https://doi.org/10.1111/jfr3.12018

Cutter, S., Emrich, C., Gall, M., & Reeves, R. (2018). Flash Flood Risk and the Paradox of Urban Development. Natural Hazards Review, 19(1), 5017005. https://doi.org/10.1061/(ASCE)NH.1527-6996.0000268

Czajkowski, J., Kunreuther,H. and Michel-Kerjan, E. 2012. A Methodological Approach for Pricing Flood Insurance and Evaluating Loss Reduction Measures: Application to Texas. Center for Risk Management, The Wharton School, Philadelphia, PA.

Dacre, H.F., M.K. Hawcroft, M.A. Stringer, and K.I. Hodges, 2012: An Extratropical Cyclone Atlas: A Tool for Illustrating Cyclone Structure and Evolution Characteristics. Bull. Amer. Meteor. Soc., 93, 1497–1502, https://doi.org/10.1175/BAMS-D-11-00164.1

Dalezios, N. R. (2017). Environmental Hazards Methodologies for Risk Assessment and Management. Water Intelligence Online, 16(January 2017), 9781780407135. https://doi.org/10.2166/9781780407135

Damm, A., Greuell, W., Landgren, O., & Prettenthaler, F. (2017). Impacts of +2 °C global warming on winter tourism demand in Europe. Climate Services. https://doi.org/10.1016/j.cliser.2016.07.003

Darwin, R. F. and Tol, R. S. J.: Estimates of the cconomic effects of sea level rise, Environ. Resour. Econ., 19(2), 113–129, doi:10.1023/A:1011136417375, 2001.

Darwin, R., Tsigas, M. E., Lewandrowski, J. and Raneses, A.: World Agriculture and Climate Change: Economic Adaptations, , (1473-2016–120700), 98 [online] Available from: http://ageconsearch.umn.edu/record/33933, 1995.

Darwin, R.: Effects of Greenhouse Gas Emissions on World Agriculture, Food Consumption, and Economic Welfare, Clim. Change, 66(1), 191–238, doi:10.1023/B:CLIM.0000043138.67784.27, 2004.

David Roodman, 2015. "EXTREME: Stata module to fit models used in univariate extreme value theory," Statistical Software Components S457953, Boston College Department of Economics, revised 18 Dec 2017.

Dawson, D., Hunt, A., Shaw, J., & Gehrels, R. (2018). The economic value of climate information in adaptation decisions: learning in the sea-level rise and coastal infrastructure context. Ecological Economics, 150, 1-10. https://doi.org/10.1016/j.ecolecon.2018.03.027

Dawson, T. P., Jackson, S. T., House, J. I., Prentice, I. C., & Mace, G. M. (2011). Beyond predictions: Biodiversity conservation in a changing climate. Science, 332(6025), 53–58. https://doi.org/10.1126/science.1200303

de Bruijn, K. M., van der Most, H., Cumiskey, L., Hounjet, M., & Mens, M. (2018). Methods and tools supporting urban resilience planning: experiences from Cork, Ireland. Journal of Geoscience and Environment Protection, 6(4), 290–309.

de Bruin, K. C., Dellink, R. B., and Tol, R. S. J. (2009a), "AD-DICE: An Implementation of Adaptation in the DICE Model", Climatic Change, 95, pp. 63–81.
de Bruin, K. C., R. B. Dellink, and S. Agrawala (2009b),. "Economic Aspects of Adaptation to Climate Change: Integrated Assessment Modelling of Adaptation Costs and Benefits." OECD Environment Working Paper, No. 6.

de Bruin, K., Dellink, R. B., Ruijs, A., Bolwidt, L., van Buuren, A., Graveland, J., ... & Tassone, V. C. (2009). Adapting to climate change in The Netherlands: an inventory of climate adaptation options and ranking of alternatives. Climatic change, 95(1-2), 23-45.

de Haan, L. and A. Ferreira, 2006: Extreme Value Theory: An Introduction. Springer Series in Operations Research and Financial Engineering, Springer, New York.

de Loyola Hummell, B. M., Cutter, S. L., & Emrich, C. T. (2016). Social Vulnerability to Natural Hazards in Brazil. International Journal of Disaster Risk Science, 7(2), 111–122. https://doi.org/10.1007/s13753-016-0090-9

De Munck, C., Pigeon, G., Masson, V., Meunier, F., Bousquet, P., Tréméac, B., … Marchadier, C. (2013). How much can air conditioning increase air temperatures for a city like Paris, France? International Journal of Climatology, 33(1), 210–227. https://doi.org/10.1002/joc.3415

De Ruiter, M. C., Ward, P. J., Daniell, J. E., & Aerts, J. C. J. H. (2017). Review Article: A comparison of flood and earthquake vulnerability assessment indicators. Natural Hazards and Earth System Sciences, 17(7), 1231–1251. https://doi.org/10.5194/nhess-17-1231-2017

de Ruiter, M. C., Couasnon, A., van den Homberg, M. J., Daniell, J. E., Gill, J. C., & Ward, P. J. (2020). Why we can no longer ignore consecutive disasters. *Earth's Future*, *8*(3), e2019EF001425.

De Vicente, J. & Crespo F. (2012). A new wildland fire danger index for a Mediterranean region and some validation aspects. International Journal of Wildland Fire, 21(8), 1030-1041. https://doi.org/10.1071/WF11046

Della-Marta, P. M., Wanner, H. (2006). A method of homogenising the extremes and mean of daily temperature measurements, Journal of climate, 19, 4179–4197.

Dellink, R., Lanzi, E., & Chateau, J. (2019). The Sectoral and Regional Economic Consequences of Climate Change to 2060. Environmental and Resource Economics, 72(2), 309–363. https://doi.org/10.1007/s10640-017-0197-5

Deltares. (2009, December). ORCA: Spatial statistical analysis. Retrieved from Deltares - Publications: http://publications.deltares.nl/1200266_003.pdf

Deltares. 2018a. Report 11200758-002. Hendriks, D. M. D., P. Trambauer, M. Mens, M. Faneca Sànchez, S. Galvis Rodriguez, H. Bootsma, C. van Kempen, M. Werner, S. Maskey, M. Svoboda, T. Tadesse, and T. Veldkamp. Global Inventory of Drought Hazard and Risk Modeling Tools.

Deltares. 2018b. Report 11200758-002. Hendriks, D. M. D., P. Trambauer, M. Mens, S. Galvis Rodriguez, M. Werner, S. Maskey, M. Svoboda, T. Tadesse, T. Veldkamp, C. Funk, and S. Shukla. Comparative Assessment of Drought Hazard and Risk Modeling Tools.

Deltares. (2020, January 22). Software: CIrcle. Retrieved from Deltares: https://www.deltares.nl/en/software/circle-critical-infrastructures-relations-and-consequences-for-life-and-environment-2/

Deltares. (2020, January 28). Deltares Atlas of Metocean Conditions. Retrieved from Metocean atlas: http://metoceanatlas.nl/

Densham, P. J. (1991). Spatial decision support systems. Geographical Information Systems. Vol. 1: Principles, 403–412.

DHI Group. (2020, February 12). Metocen Data Portal. Retrieved from DHI Group: https://www.metocean-on-demand.com/#/main

Di Paola, A., Valentini, R., & Santini, M. (2016). An overview of available crop growth and yield models for studies and assessments in agriculture: Overview of crop models for agriculture. Journal of the Science of Food and Agriculture, 96(3), 709–714. https://doi.org/10.1002/jsfa.7359

Dixon, N., Brook, E. (2007). Impact of predicted climate change on landslide reactivation: case study of Mam Tor, UK. Landslides 4, 137–147
Doak, D. F., & Morris, W. F. (2010). Demographic compensation and tipping points in climate-induced range shifts. Nature, 467(7318), 959–962. https://doi.org/10.1038/nature09439

Dobes, L (2010). Notes on Applying Real Options to Climate Change Adaptation Measures, with examples from Vietnam. Research Report No. 75. November 2010.

Dobes, L., 2008: Getting Real about Adapting to Climate Change: Using 'Real Options' to Address the Uncertainties. In: Agenda, Volume 15, Number 3, 2008, p. 55-69.

Dodgson, J. S., Spackman, M., Pearman, A., & Phillips, L. D. (2009). Multi-criteria analysis: a manual. Department for Communities and Local Government: London. From http://eprints.lse.ac.uk/12761/1/Multi-criteria_Analysis.pdf

Doetterl, S., Stevens, A., Six, J., Merckx, R., Van Oost, K., Casanova Pinto, M., Casanova-Katny, A., Munoz, C., Boudin, M., Zagal Venegas, E., & Boeckx, P. (2015). Soil carbon storage controlled by interactions between geochemistry and climate. Nat Geoscience, 8(10), 780–783.

Donatelli, M., Srivastava, A. K., Duveiller, G., Niemeyer, S., & Fumagalli, D. (2015). Climate change impact and potential adaptation strategies under alternate realizations of climate scenarios for three major crops in Europe. Environmental Research Letters, 10(7), 075005. https://doi.org/10.1088/1748-9326/10/7/075005

Dong, Z., Pan, Z., An, P., Wang, L., Zhang, J., He, D., Han, H. and Pan, X. 2015. A novel method for quantitatively evaluating agricultural vulnerability to climate change. Ecological Indicators. 48, pp.49–54.

Dosio, A. (2016). Projections of climate change indices of temperature and precipitation from an ensemble of bias-adjusted high-resolution EURO-CORDEX regional climate models. Journal of Geophysical Research: Atmospheres, 121(10), 5488-5511.

Dosio, A., & Fischer, E. M. (2018). Will half a degree make a difference? Robust projections of indices of mean and extreme climate in Europe under 1.5 C, 2 C, and 3 C global warming. Geophysical Research Letters, 45(2), 935-944

Dracup, J., Lee, K., & Paulson, E. (1980). On the definition of droughts. Water Resources Research, 16(2), 297– 302. https://doi.org/10.1029/WR016i002p00297

Dregne, H.E. (2002). Land degradation in the drylands. Arid Land Resource Management, 16,99–132.

Drouet L., Bosetti V., Tavoni M. (2015), "Selection of climate policies under the uncertainties in the Fifth Assessment Report of the IPCC", Nature Climate Change 5:937–940

Eboli, F., Parrado, R. and Roson, R.: Climate-change feedback on economic growth: explorations with a dynamic general equilibrium model, Environ. Dev. Econ., 15(5), 515–533, doi:10.1017/S1355770X10000252, 2010.

EC (2018) INDRIX – Inclusive Disaster Resilience Index, European Commission. Available at: http://indrix.samaritan-international.eu/project-results-documents/ (Accessed: 30 November 2018).
EC, MEDA Water, and MEDROPLAN (European Commission – Europe Aid Co-operation Office Euro-Mediterranean Regional Programme for Local Water Management [MEDA Water], and Mediterranean Drought Preparedness and Mitigation Planning [MEDROPLAN]). 2007. Drought Management Guidelines.

ECA (2009). Shaping Climate-resilient Development a framework for decision-making. A report of the economics of climate Adaptation working group. Economics of Climate Adaptation.

Eckstein, D., Hutfils, M.-L. and Winges, M. (2019) GLOBAL CLIMATE RISK INDEX 2019 Who Suffers Most From Extreme Weather Events? Weather-related Loss Events in 2017 and 1998 to 2017. GERMANWATCH.

ECONADAPT. Tool for Multi-Criteria Analysis of Adaptation Options | ECONADAPT Toolbox. Retrieved 4 January 2020, from https://econadapt-toolbox.eu/tool-multi-criteria-analysis-adaptation-options

EEA, 2012. Evaluation of progress under the EU National Emission Ceilings Directive — Progress towards EU air quality objectives, EEA Technical Report No 14/2012, European Environment Agency. htttp://www.eea.europa.eu/publications/evaluation-progress-nec-2012.

EEA (2015) National monitoring, reporting and evaluation of climate change adaptation in Europe (No. 20/2015). Edited by P. Pringle *et al.* Luxembourg: European Environment Agency. doi: 10.2800/629559.

EEA (2017) Report N. 15/2017. Climate change adaptation and disaster risk reduction in Europe. Enhancing coherence of the knowledge base, policies and practices.

EEA (2017). Report N. 15/2017. Climate change adaptation and disaster risk reduction in Europe. Enhancing coherence of the knowledge base, policies and practices.

EEA (2018). EEA CCIV survey – Responses, accompanying the EEA Report No 1/2018 National climate change vulnerability and risk assessments in Europe, 2018. European Environment Agency. https://www.eea.europa.eu/publications/national-climate-change-vulnerability-2018/eea-cciv-survey-responses/view

EEA (2019) Climate-ADAPT, European Environment Agency. Available at: https://climate-adapt.eea.europa.eu/about (Accessed: 7 March 2019).

Elith, J., C. H. Graham, R. P. Anderson, M. Dudík, S. Ferrier, A. Guisan, R. J. Hijmans, F. Huettmann, J. R. Leathwick, A. Lehmann, J. Li, L. G. Lohmann, B. A. Loiselle, G. Manion, C. Moritz, M. Nakamura, Y. Nakazawa, J. McC. M. Overton, A. Townsend Peterson, S. J. Phillips, K. Richardson, R. Scachetti-Pereira, R. E. Schapire, J. Soberón, S. Williams, M. S. Wisz, and N. E. Zimmermann. 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29:129–151.

Ellison, A. M. (2004). Bayesian inference in ecology. *Ecology letters*, *7*(6), 509-520.

Emmerling, J., Drouet, L., van der Wijst, K.I., Van Vuuren, D., Bosetti, V. and M. Tavoni (2019), "The Role of the Discount Rate for Emission Pathways and Negative Emissions", Environmental Research Letters14 : 1–11

Engle, N. (2011) 'Adaptive capacity and its assessment', Global Environmental Change, 21(2), pp. 647–656. doi: 10.1016/j.gloenvcha.2011.01.019.
Environmental Protection Agency (2016). Climate change indicators in the United States - Fourth edition. EPA 430-R-16-004.

Ericson, C. (2005). Hazard Analysis Techniques for System Safety. Hazard Analysis Techniques for System Safety. https://doi.org/10.1002/0471739421.ch13

Ermert, V., Fink, A.H., Jones, A.E. *et al.* Development of a new version of the Liverpool Malaria Model. I. Refining the parameter settings and mathematical formulation of basic processes based on a literature review. Malar J 10, 35 (2011) doi:10.1186/1475-2875-10-35

ESPON (2011) 'ESPON CLIMATE-Climate Change and Territorial Effects on Regions and Local Economies'. Luxembourg.

Essenfelder, A. H., Dionisio Pérez-Blanco, C., & Mayer, A. S. (2018). Rationalizing Systems Analysis for the Evaluation of Adaptation Strategies in Complex Human-Water Systems. Earth's Future, 6, 1–26. https://doi.org/10.1029/2018EF000826

European Commission (2008). "Package of Implementation Measures for the EU's Objectives on Climate Change and Renewable Energy for 2020" Commission Staff working document SEC (2008) 85 II.

European Commission (2010). "Analysis of Options to Move Beyond 20% Greenhouse Gas Emission Reductions and Assessing the Risk of Carbon Leakage" Commission Staff working document SEC (2010) 650.

European Commission (2018), "In depth analysis in support of the Commission Communication COM(2018) 773", Bruxelles
EUROPEAN COMMISSION (2018). Climate change adaptation of major infrastructure projects
https://ec.europa.eu/regional_policy/sources/docgener/studies/pdf/climate_change_major_projects/climate_change_adaptation_of_major_infrastructure_projects.pdf

European Commission, Joint Research Centre (2019): Global shoreline change projections. European Commission, Joint Research Centre (JRC) [Dataset] doi:10.2905/18EB5F19-B916-454F-B2F5-88881931587E PID: http://data.europa.eu/89h/18eb5f19-b916-454f-b2f5-88881931587e

Ewert, F., Rötter, R. P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K. C., Olesen, J. E., van Ittersum, M. K., Janssen, S., Rivington, M., Semenov, M. A., Wallach, D., Porter, J. R., Stewart, D., Verhagen, J., Gaiser, T., Palosuo, T., Tao, F., Nendel, C., Roggero, P.P., Bartosova, L., Asseng, S. (2015). Crop modelling for integrated assessment of risk to food production from climate change. Environmental Modelling & Software, 72, 287–303. https://doi.org/10.1016/j.envsoft.2014.12.003

EXTREMES. (2009, May 7). Retrieved from Mistis: http://extremes.gforge.inria.fr/#References

Eyckmans, J. and Tulkens, H. (2003). "Simulating Coalitionally Stable Burden Sharing Agreements for the Climate Change Problem", Resource and Energy Economics, 25, pp. 299–327

Fabbri, K. P. (1998). A methodology for supporting decision making in integrated coastal zone management. Ocean & Coastal Management, 39(1–2), 51–62.
Faggian, P. (2018). Estimating fire danger over Italy in the next decades. Euro-Mediterranean Journal for Environmental Integration, 3, 15
https://doi.org/10.1007/s41207-018-0053-1

Fang, Z., Bailey, R.L., & Shiver, B.D. (2001). A multivariate simultaneous prediction system for stand growth and yield with fixed and random effects. For. Sci., 47(4), 550–562.

FAO. 2012. The state of the world fisheries and aquaculture - 2012. Rome.

Feddema, J., Mills, G., & Ching, J. (2015). Demonstrating the added value of WUDAPT for Urban Climate Modelling. 19(2012), 15889.

Fekete, A. (2009) 'Validation of a social vulnerability index in context to river-floods in Germany', Natural Hazards and Earth System Science, 9(2), pp. 393–403. doi: 10.5194/nhess-9-393-2009.

Fekete, A., Damm, M. and Birkmann, J. 2009. Scales as a challenge for vulnerability assessment. Natural Hazards. 55(3), pp.729–747.

Felgenhauer T, de Bruin KC (2009) Optimal paths of climate change mitigation and adaptation under certainty and uncertainty. International Journal of Global Warming 1:66–88

Fernandez, M., Bucaram, S. and Renteria, W. (2017) '(Non-) robustness of vulnerability assessments to climate change: An application to New Zealand', Journal of Environmental Management, 203(1), pp. 400–412. doi: 10.1016/j.jenvman.2017.07.054.

Fernandez, P., Mourato, S., & Moreira, M. (2016). Social vulnerability assessment of flood risk using GIS-based multicriteria decision analysis. A case study of Vila Nova de Gaia (Portugal). Geomatics, Natural Hazards and Risk, 7(4), 1367–1389.
https://doi.org/10.1080/19475705.2015.1052021

Feyen L., Ciscar J.C., Gosling S., Ibarreta D., Soria A. (editors) (2020). Climate change impacts and adaptation in Europe. JRC PESETA IV final report. EUR 30180EN, Publications Office of the European Union, Luxembourg, ISBN 978-92-76-18123-1, doi:10.2760/171121, JRC119178.

Finney, M.A. (1998). FARSITE: Fire Area Simulator – model development and evaluation. Rocky Mountain Research Station Research, RMRS-RP-4. Fort Collins, CO: USDA Forest Service

Finney, M.A. (2006). An overview of FlamMap fire modeling capabilities. In P.L. Andrews, B.W. Butler (eds.). Fuels Management – How to Measure Success: Conference Proceedings (pp. 213–220). Rocky Mountain Research Station, RMRS-P 41. Fort Collins, CO: USDA Forest Service

Fioravanti, G., Piervitali, E., & Desiato, F. (2016). Recent changes of temperature extremes over Italy: an index-based analysis. Theoretical and applied climatology, 123(3-4), 473-486

Fischer, E. M., Beyerle, U., & Knutti, R. (2013). Robust spatially aggregated projections of climate extremes. Nature Climate Change, 3(12), 1033-1038.
Fischer, E. M., Sedláček, J., Hawkins, E., & Knutti, R. (2014). Models agree on forced response pattern of precipitation and temperature extremes. Geophysical Research Letters, 41(23), 8554-8562.

Fischer, E.M., Schär C. (2009). Future Changes in daily summer temperature variability: driving processes and role for temperature extremes. Climate Dynamics, 33(7), 917–935

Fischer, E.M., Schär, C. (2010). Consistent geographical patterns of changes in high-impact European heatwaves. Nature Geoscience 3(6), 398–403

Fisher, R.A. and Tippett, L.H.C. (1928) Limiting Forms of the Frequency Distribution of the Largest or Smallest Members of a Sample. Proceedings of the Cambridge Philosophical Society, 24, 180-190.

Flannigan, M.D. & VanWagner, C.E. (1991). Climate change and wildfire in Canada. Canadian Journal of Forest Research, 21, 66– 72.

Fonderflick, J., Lepart, J., Caplat, P., Debussche, M. & Marty, P. (2010). Managing agricultural change for biodiversity conservation in a Mediterranean upland. Biological Conservation, 143(3), 737–746.

Fontes, L., Bontemps, J., Bugmann, H., Van Oijen, M., Gracia, C., Kramer, K., Lindner, M., Rötzer, T., Peter Skovsgaard, J. l (2010) Models for supporting forest management in a changing environment. Forest Systems, 19, 8–29.

Forzieri, G., Bianchi, A., e Silva, F.B., Herrera, M.A.M., Leblois, A., Lavalle, C., Aerts, J.C. and Feyen, L., 2018. Escalating impacts of climate extremes on critical infrastructures in Europe. Global environmental change, 48, pp.97-107.

Frazier, T.G., Thompson, C.M. and Dezzani, R.J. 2014. A framework for the development of the SERV model : A Spatially Explicit Resilience-Vulnerability model. Applied Geography. 51, pp.158–172.

Fried, J., Gilless, W., Riley, T., Moody, C., Simon, K., Hayhoe, M., Moritz, M., Stephens, S., Torn, M. (2008). Predicting the effect of climate change on wildfire behaviour and initial attack success. Climatic Change, 87, 193–213. https://doi.org/10.1007/s10584-007-9360-2

Frisch, R. (1938). Autonomy of Economic Relations. Statistical versus Theoretical Relations in Economic Macrodynamics. in Hendry, D. F. and Morgan, M.S. (1995). The Foundations of Econometric Analysis, Cambridge University Press, Cambridge (UK).

Fujimori, S., Iizumi, T., Hasegawa, T., Takakura, J., Takahashi, K. and Hijioka, Y.: Macroeconomic Impacts of Climate Change Driven by Changes in Crop Yields, Sustainability, 10(10), 3673, doi:10.3390/su10103673, 2018.

Fujimori, S., Masui, T., Matsuoka, Y. (2012), AIM/CGE [basic] manual. Discussion paper series, 2012-01, Center for Social and Environmental Systems Research, National Institute

Fulton, E. A. 2010. Approaches to end-to-end ecosystem models. Journal of Marine Systems 81:171–183.

Furlan, E., Slanzi, D., Torresan, S., & Critto, A. (2019). Multi-scenario analysis in the Adriatic Sea : a GIS-based Bayesian Network to support maritime spatial planning. Science of the Total Environment, (xxxx), 134972. https://doi.org/10.1016/j.scitotenv.2019.134972

G. Guimarães Nobre G, Davenport F, Bischiniotis K, Veldkamp T, Jongam B, Funk C, Husak G, Ward P and Aerts J. Financing agricultural drought risk through ex-ante cash transfers Science ofthe Total Environment 653 523–535

Gallina, V., Torresan, S., Critto, A., Sperotto, A., Glade, T., & Marcomini, A. (2016). A review of multi-risk methodologies for natural hazards: Consequences and challenges for a climate change impact assessment. Journal of Environmental Management, 168, 123–132. https://doi.org/10.1016/j.jenvman.2015.11.011

Gallina, V., Torresan, S., Zabeo, A., Rizzi, J., Carniel, S., Sclavo, M., … Critto, A. (2019). Assessment of Climate Change Impacts in the North Adriatic Coastal Area. Part II: Consequences for Coastal Erosion Impacts at the Regional Scale. Water, 11(6), 1300.

GARCIA DE CORTAZAR-ATAURI I., 2006. Adaptation dumodèle STICS à la vigne (Vitis viniferaL.). Utilisation dansle cadre d'une étude d'impact du changement climatique àl'échelle de la France. PhD thesis, Montpellier, SupAgro.

García, L.E., J.H. Matthews, D.J. Rodriguez, M. Wijnen, K.N. DiFrancesco, P. Ray. ,2014 : Beyond Downscaling: A Bottom-Up Approach to Climate Adaptation for Water Resources Management. AGWA Report 01. Washington, DC: World Bank Group.

Gariano, S. L., & Guzzetti, F. (2016). Landslides in a changing climate. Earth-Science Reviews, 162, 227-252.

Gariano, S. L., Petrucci, O., & Guzzetti, F. (2015). Changes in the occurrence of rainfall-induced landslides in Calabria, southern Italy, in the 20th century. Nat. Hazards Earth Syst. Sci, 15, 2313-2330.

Gariano, S. L., Rianna, G., Petrucci, O., & Guzzetti, F. (2017). Assessing future changes in the occurrence of rainfall-induced landslides at a regional scale. Science of the total environment, 596, 417-426.

Gencay, R., Selçuk, F., & Ulugülyagci, A. (2001). EVIM: A Software Package for Extreme Value Analysis in MATLAB. Studies in Nonlinear Dynamics & Econometrics, 5.

Gerl, T., Kreibich, H., Franco, G., Marechal, D. and Schröter, K., 2016. A review of flood loss models as basis for harmonization and benchmarking. PloS one, 11(7), p.e0159791.

Gersonius, B., Ashley, R. Pathirana, A., and Zevenbergen, C. (2013). Climate change uncertainty: building flexibility into water and flood risk infrastructure. Climatic Change, 116: 411. https://doi.org/10.1007/s10584-012-0494-5

Giannakopoulos, C., Karali, A., Roussos, A. (2014). Tailored stakeholder products help provide a vulnerability and adaptation assessment of Greek forests due to climate change. Geophysical Research Abstracts, 16, EGU2014-6536

Giannakopoulos, C., LeSager, P., Moriondo, M., Bindi, M., Karali, A., Hatzaki, M., Kostopoulou, E. (2012). Comparison of fire danger indexes in the Mediterranean for present day conditions. iForest, 5, 197-203. https://doi.org/10.3832/ifor0622-005

Giannaros, C., Nenes, A., Giannaros, T. M., Kourtidis, K., & Melas, D. (2018). A comprehensive approach for the simulation of the Urban Heat Island effect with the WRF/SLUCM modeling system: The case of Athens (Greece). Atmospheric Research, 201(October 2017), 86–101. https://doi.org/10.1016/j.atmosres.2017.10.015

Gilbert, N., & Troitzsch, K. (2005). *Simulation for the social scientist*. McGraw-Hill Education (UK).

Gill, J. C., & Malamud, B. D. (2016). Hazard interactions and interaction networks (cascades) within multi-hazard methodologies. Earth System Dynamics, 7(3), 659–679. https://doi.org/10.5194/esd-7-659-2016

Gill, S. E., Handley, J. F., Ennos, A. R., & Pauleit, S. (2007). Adapting cities for climate change the role of the green infrastructure.pdf. Built Environment, 115–133. https://doi.org/10.2148/benv.33.1.115

Gilleland, E., M. Ribatet and A. G. Stephenson, 2013: A software review for extreme value analysis. Extremes, 16 (1), 103 - 119, DOI: 10.1007/s10687-012-0155-0 (pdf).

Gilleland, E. & Katz, R. W. extremes 2.0: An extreme value analysis package in r. Journal of Statistical Software 72, 1–39 (2016).

Gilroy, K., & Jeuken, A. J. C. S. (2018). Collaborative Risk Informed Decision Analysis: A water security case study in the Philippines. 11, 62-71.

Giorgi, F., Coppola, E., & Raffaele, F. (2014). A consistent picture of the hydroclimatic response to global warming from multiple indices: Models and observations. Journal of Geophysical Research Atmospheres, 119(20), 11-695.

Gjerde J, Grepperud S, Kverndokk S (1999), “Optimal climate policy under the possibility of a catastrophe”, Resource and Energy Economics 21(3–4):289–317

Glavan, M., Ceglar, A., Pintar, M. (2015). Assessing the impacts of climate change on water quantity and quality modelling in small Slovenian Mediterranean catchment – lesson for policy and decision makers, Hydrological Processes, 29, 3124–3144.

Glick, P., B. A. Stein, and N. A. Edelson, 2011: Scanning the conservation horizon: A guide to climate change vulnerability assessment. National Wildlife Federation Publ., 168 pp., www.nwf.org/~/media/pdfs /global-warming/climate-smart-conservation/nwf scanningtheconservationhorizonfinal92311.ashx

Golub, A. A., Henderson, B. B., Hertel, T. W., Gerber, P. J., Rose, S. K. and Sohngen, B.: Global climate policy impacts on livestock, land use, livelihoods, and food security., Proc. Natl. Acad. Sci. U. S. A., 110(52), 20894–9, doi:10.1073/pnas.1108772109, 2013.

Gosling S.N., Zaherpour J., Ibarreta D., PESETA III: Climate change impacts on labour productivity, EUR 29423 EN, Publications Office of the European Union, Luxembourg, 2018, ISBN 978-92-79-96912-6, doi:10.2760/07911, JRC113740

Grebner, D.L., Bettinger, P., & Siry, J.P. (2013). Forest Dynamics. In: Introduction to Forestry and Natural Resources. Amsterdam: Elsevier.

Griffith, G. P., E. A. Fulton, R. Gorton, and A. J. Richardson. 2012. Predicting Interactions among Fishing, Ocean Warming, and Ocean Acidification in a Marine System with Whole-Ecosystem Models. Conservation Biology 26:1145–1152.

Grijsen et al, 2014:Climate Risk Assessment of the Niger River Basin Sustainable Development Action Plan, Final Report, Volumes 1 – 5; published on website Niger Basin Authority (http://www.abn.ne/CRA-SDAP

Grimmond, C. S. B., & Oke, T. R. (2002). Turbulent heat fluxes in urban areas: Observations and a local-scale urban meteorological parameterization scheme (LUMPS). Journal of Applied Meteorology, 41(7), 792–810. https://doi.org/10.1175/1520-0450(2002)041<0792:THFIUA>2.0.CO;2

Grimmond, C. S. B., Blackett, M., Best, M. J., Barlow, J., Baik, J. J., Belcher, S. E., … Zhang, N. (2010). The international urban energy balance models comparison project: First results from phase 1. Journal of Applied Meteorology and Climatology, 49(6), 1268–1292. https://doi.org/10.1175/2010JAMC2354.1

Gritti, E.S., Smith, B. and Sykes, M.T. 2006. Vulnerability of Mediterranean Basin ecosystems to climate change and invasion by exotic plant species. , pp.145–157.

Groves, D. G., Molina-Perez, E., Bloom, E., & Fischbach, J. R. (2019). Robust Decision Making (RDM): Application to Water Planning and Climate Policy. In Decision Making under Deep Uncertainty (pp. 135-163): Springer.

Groves, D.G. and Sharon, C. (2013). Planning Tool to Support Planning the Future of Coastal Louisiana. Journal of Coastal Research: Special Issue 67, pp147-161.- Louisiana's 2012 Coastal Master Plan Technical Analysis:147-161.2013. DOI10.2307/23486542

GWP CEE (Global Water Partnership Central and Eastern Europe). 2015. Guidelines for Preparation of Drought Management Plans: Development and Implementation in the Context of the EU Water Framework Directive. Global Water Partnership Central and Eastern Europe, 48 pp.

Haasnoot, M., Brown, S., Scussolini, P., Jimenez, J. A., Vafeidis, A. T., & Nicholls, R. J. (2019). Generic adaptation pathways for coastal archetypes under uncertain sea-level rise. Environmental Research Communications, 1(7), 71006. https://doi.org/10.1088/2515-7620/ab1871

Haasnoot M., Warren A., Kwakkel J.H. (2019) Dynamic Adaptive Policy Pathways (DAPP). In: Marchau V., Walker W., Bloemen P., Popper S. (eds) Decision Making under Deep Uncertainty. Springer, Cham

Haer, T., Botzen, W.J.W., Aerts, J.C.J.H. (2019a). Advancing disaster policies by integrating dynamic adaptive behaviour in risk assessments using an agent-based modelling approach. Environmental Research Letters, 14:4.

Haer, T., Botzen, W.J.W., de Moel, H., Aerts, J.C.J.H. (2017). Integrating household risk mitigation behaviour in flood risk analysis: An agent-based model approach. Risk Analysis, 37(10): 1977-1992.

Haer, T., Husby, T., Botzen, W.J.W., Aerts, J.C.J.H. (2019b). The safe development paradox: An agent-based model for flood risk under climate change in the European Union. Global Environmental Change, 60: 102009.
Hailegiorgis, A., Crooks, A., Cioffi-Revilla, C. (2018). An Agent-Based Model of rural households' adaptation to climate change. Journal of Artificial Societies & Social Simulation, 21(4): 4.

Haines, D.A., Main, W.A., Frost, J.S., Simard, A.J. (1983). Fire-danger rating and wildfire occurrence in the northeastern United States. Forest Science, 66, 159-164. Retrieved from http://academic.oup. com/forestscience/article-abstract/29/4/679/46 56770

Hajat, S. Vardoulakis, S. Heaviside, C. Eggen, B (2014). Climate Change effects on human health: projections of temperature-related mortality for the UK during the 2020s, 2050s and 2080s. JECH, Feb 2014. 10.1136/jech-2013-202449.

Hallegatte, S. (2014). Decision making for disaster risk management in a changing climate. In Natural disasters and climate change (pp. 177-194): Springer.

Hames, D. and S. Vardoulakis (2012). Climate Change Risk Assessment for the Health Sector. January 2012. Defra Project Code GA0204.

Hamilton, J. M., Maddison, D. J., & Tol, R. S. J. (2005). Climate change and international tourism: a simulation study. Global Environmental Change, 15(3), 253–266. https://doi.org/10.1016/j.gloenvcha.2004.12.009

Harley, S. J., and R. A. Myers. 2001. Hierarchical bayesian models of length-specific catchability of research trawl surveys. Canadian Journal of Fisheries and Aquatic Sciences 58:1569–1584.

Hashimoto, T., Stedinger, J. R., & Loucks, D. P. (1982). Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation. Water Resources Research, 18(1), 14–20.

Hassani-Mahmooei, B., Parris, B. W. (2012). Climate change and internal migration patterns in Bangladesh: An agent-based model. Environment and Development Economics, 17(6): 763–780.

Hawkins E. , Sutton R. (2009). The potential to narrow uncertainty in regional climate predictions. Bulletin of the American Meteorological Society 90 (8), 1095-1107.

Hawkins E. , Sutton R. (2011). The potential to narrow uncertainty in projections of regional precipitation change. Climate Dynamics 37 (1), 407-418.

Haylock, M. R., N. Hofstra, A. M. G. Klein Tank, E. J. Klok, P. D. Jones, and M. New (2008). A European daily high-resolution gridded data set of surface temperature and precipitation for 1950-2006, J. Geophys. Res., 113

He, Q., Yang, X.H., Mamtimin, A., & Tang, S. (2011). Impact factors of soil wind erosion in the center of Taklimakan desert. Journal of Arid Land, 3,9–14.

Health England, P. (2018). Heatwave mortality monitoring - Summer 2018. Retrieved from www.facebook.com/PublicHealthEngland

Heinsch, F.A. & Andrews, P.L. (2010). BehavePlus fire modeling system version 5.0: Design and Features. Rocky Mountain Research Station, RMRS-GTR-249. Fort Collins, CO: USDA Forest Service
Heintze, H.-J. *et al.* (2018) 'World Risk Report', Bündnis Entwicklung Hilf, Ruhr University Bochum. Available at: https://weltrisikobericht.de/english-2/ (Accessed: 3 December 2018).

Herold, N., Behrangi, A., & Alexander, L. V. (2017). Large uncertainties in observed daily precipitation extremes over land. Journal of Geophysical Research: Atmospheres, 122(2), 668-681.

Herawati, H., González-Olabarria, J.R., Wijaya, A., Martius, C., Purnomo, H., Andriani, R. (2015). Tools for Assessing the Impacts of Climate Variability and Change on Wildfire Regimes in Forests. Forests, 6(5), 1476-1499. https://doi.org/10.3390/f6051476

Hinkel, J., 2005. DIVA: an iterative method for building modular integrated models. Advances in Geosciences 4, 45-50.

Ho, K., Lacasse, S., & Picarelli, L. (2017). Slope Safety Preparedness for Impact of Climate Change. CRC Press.

Hobbs, J. (1987). Climatic hazards. Encycl Climatol, 7, 279-287.

Hof A., F., de Bruin, K. C., Dellink, R. B., den Elzen, M. G. J., and van Vuuren, D. P. (2009). "The Effect of Different Mitigation Strategies on International Financing of Adaptation", Environmental Science and Policy, 12, pp. 832–843.

Hof, A., van Vuuren, D., Watkiss, P., Hunt, A. (2018). D1.5 Impact and policy scenarios co-designed with stakeholders. Deliverable of the H2020 COACCH project
Hoffman, C.M., Sieg, C.H., Linn, R.R., Mell, W., Parsons, R.A., Ziegler, J.P., Hiers, J.K. (2018). Advancing the science of wildland fire dynamics using process-based models. Fire, 1(2), 32. https://doi.org/10.3390/fire1020032

Holland GJ (1980) An analytic model of the wind and pressure profiles in hurricanes. Mon Weather Rev 108:1212–1218. doi:10.1175/1520-0493(1980)108<1212:AAMOTW>2.0.CO;2

Holleman, I. (2001). Hail detection using single-polarization radar. KNMI.

Holzworth, D. P., Huth, N. I., deVoil, P. G., Zurcher, E. J., Herrmann, N. I., McLean, G., … Keating, B. A. (2014). APSIM – Evolution towards a new generation of agricultural systems simulation. Environmental Modelling & Software, 62, 327–350. https://doi.org/10.1016/j.envsoft.2014.07.009

Holzworth, D. P., Snow, V., Janssen, S., Athanasiadis, I. N., Donatelli, M., Hoogenboom, G., White, J. W., Thorburn, P. (2015). Agricultural production systems modelling and software: Current status and future prospects. Environmental Modelling & Software, 72, 276–286. https://doi.org/10.1016/j.envsoft.2014.12.013

Hong, Y. I. N., & Ying, S. U. N. (2018). Characteristics of extreme temperature and precipitation in China in 2017 based on ETCCDI indices. Advances in Climate Change Research, 9(4), 218-226

Hoogenboom, G. (1994). Computer simulation in biology: A BASIC introduction. Agricultural Systems, 44(4), 476–478. https://doi.org/10.1016/0308-521X(94)90200-Y

Hoogenboom, G., Porter, C.H., Shelia, V., Boote, K.J., Singh, U., White, J.W., Hunt, L.A., Ogoshi, R., Lizaso, J.I., Koo, J., Asseng, S., Singels, A., Moreno, L.P., & Jones, J.W. (2019). Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7.5. DSSAT Foundation, Gainesville, Florida, USA. Retrieved from https://DSSAT.net.

Hope, C. (2006). "The Marginal Impact of CO2 from PAGE2002: An Integrated Assessment Model Incorporating the IPCC's Five Reasons for Concern." The Integrated Assessment Journal, 6 (1), pp. 19–56.

Hope, C. (2009). "The Costs and Benefits of Adaptation". In Assessing the Costs of Adaptation to Climate Change: A Review of the UNFCCC and Other Recent Estimates, IIED, London, pp. 100–110.

Hope, C . (2011), "The Social Cost of CO2 from the PAGE09 Model", Economics ejournal discussion papers 2011-39

Hope, C., Anderson, J., and Wenman, P. (1993). "Policy Analysis of the Greenhouse Effect: An Application of the PAGE Model." Energy Policy, 21 (3), pp. 327–338.

Houet, T., Marchadier, C., Bretagne, G., Moine, M. P., Aguejdad, R., Viguié, V., … Masson, V. (2016). Combining narratives and modelling approaches to simulate fine scale and long-term urban growth scenarios for climate adaptation. Environmental Modelling and Software, 86, 1–13. https://doi.org/10.1016/j.envsoft.2016.09.010

Hounjet, M., Kieftenburg, A., & Altamirano, M. (2016). Learning from flood events on Critical Infrastructure: Relations and Consequences for Life and Environment (CIrcle). Coast. Manag.

Hov, Ø., Cubasch, U., Fischer, E., Höppe, P., Iversen, T., Gunnar Kvamstø, N., ... & Schädler, B. (2013). Extreme weather events in Europe: preparing for climate change adaptation. Norwegian Meteorological Institute

Howard, P. H., & Sterner, T. (2017). Few and Not So Far Between: A Meta-analysis of Climate Damage Estimates. Environmental and Resource Economics, 68(1), 197–225. https://doi.org/10.1007/s10640-017-0166-z

Hu, X., J.W. Hall, P. Shi, and W.H. Lim. 2016. The spatial exposure of the Chinese infrastructure system to flooding and drought hazards. Natural Hazards 80(2): 1083–1118.

Hudson, P. (2018). A comparison of definitions of affordability for flood risk adaption measures: a case study of current and future risk-based flood insurance premiums in Europe. Mitigation and Adaptation Strategies for Global Change, 23(7): 1019-1038.

Hudson, P., Botzen, W.J.W., Aerts, J.C.J.H. (2019). Flood insurance arrangements in the European Union for future flood risk under climate and socio-economic change. Global Environmental Change, 58:101966.

Hudson, P., Botzen, W.J.W., Feyen, L., Aerts, J.C.J.H. (2016). Incentivising flood risk adaptation through risk based insurance premiums: trade-offs between affordability and risk reduction. Ecological Economics, 125: 1-13.

Hufschmidt, G. (2011). A comparative analysis of several vulnerability concepts. Natural hazards, 58(2), 621-643.
HYPE. (2016). HYPE Model Documentation: Setting up a HYPE model domain - a beginner's tutorial. Retrieved June 11, 2017, from SMHI HYPE Model Documentation website:
http://www.smhi.net/hype/wiki/doku.php?id=start:hype_tutorials:hype_setup_tutorial

Iglesias A., Moneo M., Quiroga S. Methods for evaluating social vulnerability to drought [Part 1. Components of drought planning. 1.3. Methodological component] . In : Iglesias A. (ed.), Moneo M. (ed.), López-Francos A. (ed.). Drought management guidelines technical annex. Zaragoza : CIHEAM / EC MEDA Water, 2007. p. 129-133 (Options Méditerranéennes : Série B. Etudes et Recherches; n. 58)

IMPACT2C (2015). Deliverable D8.1 Design and production of an ensemble of air quality simulations and evaluation of health impacts. Deliverable of the IMPACT2C project.

Imsland, A. K., A. Foss, A. Folkvord, S. O. Stefansson, and T. M. Jonassen. 2005. The interrelation between temperature regimes and fish size in juvenile Atlantic cod (Gadus morhua): Effects on growth and feed conversion efficiency. Fish Physiology and Biochemistry 31:347–361.

INFORM - Global, open-source risk assessment for humanitarian crises and disasters (2018) European Commission. Available at: http://www.inform-index.org/ (Accessed: 3 December 2018).

Inostroza, L., Palme, M., de la Barrera, F. (2016). A Heat Vulnerability Index: Spatial Patterns of Exposure, Sensitivity and Adaptive Capacity for Santiago de Chile. PLoS ONE 11(9), e0162464

IPCC 2007. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. . Geneva, Switzerland: IPCC.

IPCC (2012) Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change [Field, C.B., V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 582 pp.

IPCC (2013) Climate change 2013: The physical science basis: Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom

IPCC (2013). Climate change 2013: The physical science basis: Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, United Kingdom

IPCC. (2018). Global Warming of 1.5° C: An IPCC Special Report on the Impacts of Global Warming of 1.5° C Above Pre-industrial Levels and Related Global Greenhouse

Gas Emission Pathways, in the Context of Strengthening the Global Response to the Threat of Climate Chang. Intergovernmental Panel on Climate Change.

Izaurralde, R. C., Williams, J. R., McGill, W. B., Rosenberg, N. J., & Jakas, M. C. Q. (2006). Simulating soil C dynamics with EPIC: Model description and testing against long-term data. Ecological Modelling, 192(3–4), 362–384. https://doi.org/10.1016/j.ecolmodel.2005.07.010

Izurralde, R.C., Williams, J.R., McGill, W.B., Rosenberg, N.J., & Jakas, M.C.Q. (2006). Simulating soil C dynamics with EPIC: model description and testing against long-term data. Ecol. Model. 192 (3-4), 362-384.

Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O. B., Bouwer, L. M., & Georgopoulou, E. (2014). EURO-CORDEX: new high-resolution climate change projections for European impact research. Regional environmental change, 14(2), 563-578.

Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O. B., Bouwer, L. M., Yiou, P. (2014). EURO-CORDEX: New high-resolution climate change projections for European impact research. Regional Environmental Change, 14, 563–578

Jan C Semenza, Jonathan E Suk, Vector-borne diseases and climate change: a European perspective, FEMS Microbiology Letters, Volume 365, Issue 2, January 2018, fnx244, https://doi.org/10.1093/femsle/fnx244

Janssen, M. (2005). 8. Agent-Based Modelling. Modelling in Ecological Economics, 155–172.

Janssen, R. (1992). Multiobjective Decision Support for Environmental Management, Environment and Management. Kluwer Academic Publishers, Dordrecht, Netherlands.

Jenkins, K., Surminski, S., Hall, J., Crick, F. (2017) Assessing surface water flood risk and management strategies under future climate change: insights from an agent-based model. Science of the Total Environment, 595: 159-168.

Jeuland, M., and D. Whittington (2014), Water resources planning under climate change: Assessing the robustness of real options for the Blue Nile, Water Resour. Res., 50, 2086–2107,

Jimeno-Sáez, P., Senent-Aparicio, J., Pérez-Sánchez, J., & Pulido-Velazquez, D. (2018). A Comparison of SWAT and ANN Models for Daily Runoff Simulation in Different Climatic Zones of Peninsular Spain. Water, 10(2), 192.

Johnson, W., Williams, Q., Kirshen, P. (1995): "WEAP: A Comprehensive and Integrated Model of Supply and Demand," Proceedings of the 1995 Georgia Water Resources Conference, Athens, Georgia, USA, April 11-12, 1995.

Jones, J. ., Hoogenboom, G., Porter, C. ., Boote, K. ., Batchelor, W. ., Hunt, L. ., Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J. T. (2003). The DSSAT cropping system model. European Journal of Agronomy, 18(3–4), 235–265. https://doi.org/10.1016/S1161-0301(02)00107-7

Jones, J. W., Antle, J. M., Basso, B., Boote, K. J., Conant, R. T., Foster, I., Godfray, H. C. J., Herrero, M., Howitt, R. E., Janssen, S., Keating, B. A., Munoz-Carpena, R., Porter, C. H., Rosenzweig, C., Wheeler, T. R. (2017). Brief history of agricultural

systems modeling. Agricultural Systems, 155, 240–254.
https://doi.org/10.1016/j.agsy.2016.05.014

Jongman, B., Hochrainer-Stigler, S., Feyen, L., Aerts, J.C.J.H., Mechler, R., Botzen, W.J.W., Bouwer, L.M., Pflug, G., Rojas, R., Ward, P. (2014). Stress on disaster finance due to correlated flood extremes. Nature Climate Change, 4: 264-268.

Jongman, B., Kreibich, H., Apel, H., Barredo, J.I., Bates, P.D., Feyen, L., Gericke, A., Neal, J., Aerts, J.C.J.H. and Ward, P.J., 2012. Comparative flood damage model assessment: towards a European approach.

Jonsson, R., Blujdea, V., Fiorese, G., Pilli, R., Rinaldi, F., Baranzelli, C., & Camia, A. (2018). Outlook of the European forest-based sector: forest growth, harvest demand, wood-product markets, and forest carbon dynamics implications. iForest - Biogeosciences and Forestry, 11(2), 315–328.

JRC (2018) JRC PESETA III, EU Science Hub. Available at: https://ec.europa.eu/jrc/en/peseta-iii (Accessed: 13 December 2019).

JRC, J. R. C. (2014). Framework service contract for operating the EFAS dissemination centre in support to the Copernicus Emergency Management Service (EMS)/Early Warning Systems (EWS). In Appendix to Technical Specifications (Invitation to tender no . JRC/IPR/2014/H.7/0039/OC).

Kainuma, M., Matsuoka, Y., and Morita, T. (2003). (Eds.) Climate Policy Assessment Asia-Pacific Integrated Modeling, Springer-Verlag.

Kalabokidis, K., Palaiologou, P., Gerasopoulos, E., Giannakopoulos, C., Kostopoulou, E., Zerefos, C. (2015). Effect of Climate Change Projections on Forest Fire Behavior and Values-at-Risk in Southwestern Greece. Forests, 6(6), 2214-2240.
https://doi.org/10.3390/f6062214

Kalra, N., Groves, D. G., Bonzanigo, L., Perez, E. M., Ramos, C., Brandon, C., & Rodriguez Cabanillas, I. (2015). Robust decision-making in the water sector: a strategy for implementing Lima's long-term water resources master plan: The World Bank.

Kappes, M., Keiler, M., & Glade, T. (2010). From Single- to Multi-Hazard Risk analyses: a concept addressing emerging challenges. Mountain risks: Bringing science to society. Proceedings of the international conference, Florence.

Kareiva, P., Watts, S., McDonald, R., & Boucher, T. (2007). Domesticated nature: Shaping landscapes and ecosystems for human welfare. Science, 316(5833), 1866–1869. https://doi.org/10.1126/science.1140170

Karl, T. R., Nicholls, N., & Ghazi, A. (1999). Clivar/GCOS/WMO workshop on indices and indicators for climate extremes workshop summary. In: Weather and Climate, Springer, Dordrecht.

Keane, R.E. & Finney, M.A. (2003). The simulation of landscape fire, climate, and ecosystem dynamics. In T.T. Veblen, W.L. Baker, G. Montenegro, T.W. Swetnam (eds.). Fire and climatic change in temperate ecosystems of the western Americas. New York, NY: Springer Verlag

Keating, B. A., Carberry, P. S., Hammer, G. L., Probert, M. E., Robertson, M. J., Holzworth, D., Huth, N.I., Hargreaves, J.N.G., Meinke, H., Hochman, Z., McLean, G., Verburg, K., Snow, V., Dimes, J.P., Silburn, M., Wang, E., Brown, S., Bristow, K.L., Asseng, S., Chapman, S., McCown, R.L., Freebairn, D.M., Smith, C. J. (2003). An overview of APSIM, a model designed for farming systems simulation. European Journal of Agronomy, 18(3–4), 267–288. https://doi.org/10.1016/S1161-0301(02)00108-9

Keetch, J.J., & Byram, G. (1968). A drought index for forest fire control. Southeastern Forest Experiment Station, SE-38. Asheville, NC: USDA Forest Service

Keith, D. A., Akçakaya, H. R., Thuiller, W., Midgley, G. F., Pearson, R. G., Phillips, S. J., … Rebelo, T. G. (2008). Predicting extinction risks under climate change: Coupling stochastic population models with dynamic bioclimatic habitat models. Biology Letters, 4(5), 560–563. https://doi.org/10.1098/rsbl.2008.0049

Kelley, D.I., Prentice, I.C., Harrison, S.P., Wang, H., Simard, M., Fisher, J.B., Willis, K.O (2013). A comprehensive benchmarking system for evaluating global vegetation models. Biogeosciences, 10, 3313–3340. https://doi.org/10.5194/bg-10-3313-2013

Kelly, S., P. Tyler, and D. Crawford-Brown. 2016. Exploring vulnerability and interdependency of UK infrastructure using key-linkages analysis. Networks and Spatial Economics 16(3): 865–892.

Kemp, R. 2016. Living without electricity: One city’s experience of coping with loss of power. London: Royal Academy of Engineering. https://www.raeng.org.uk/publications/reports/living-without-electricity. Accessed 30 Aug 2019.

Kendrovski, V., Baccini, M. Martinez, G. S., Wolf, T., Paunovic, E., and Menne, B. (2017). Quantifying Projected Heat Mortality Impacts under 21st-Century Warming Conditions for Selected European Countries. Int. J. Environ. Res. Public Health 2017, 14(7), 729; doi:10.3390/ijerph14070729.

Kepner, W.G., Rubio, J.L., Mouat, D.A., & Pedrazzini, F. (2006) Desertification in the mediterranean region: a security issue. NATO Security through Science Series (Vol. 3). Netherlands: Springer.

Keyantash, J., & Dracup, J. (2002). The quantification of drought: An evaluation of drought indices. Bulletin of the American Meteorological Society, 83(8), 1167–1180. https://doi.org/10.1175/1520-0477-83.8.1167

Khabarov, N., Krasovskii, A., Obersteiner, M., Swart, R., Dosio, A., san-Miguel-Ayanz, J., Durrant, T., Camia, A., Migliavacca, M. (2016). Forest fires and adaptation options in Europe. Regional Environmental Change, 16, 21–30. https://doi.org/10.1007/s10113-014-0621-0

Kharin, V. V., F. W. Zwiers, X. Zhang, and G. C. Hegerl (2007). Changes in temperature and precipitation extremes in the IPCC ensemble of global coupled model simulations, J. Climate, 20, 1419–1444

Kind, J., Wouter Botzen, W. J. & Aerts, J. C. J. H. Accounting for risk aversion, income distribution and social welfare in cost-benefit analysis for flood risk management. WIREs Clim. Chang. 8, e446 (2017).

Kingsborough A. *et al.* (2017). Development and appraisal of long-term adaptation pathways for managing heat-risk in London. Climate Risk Management 16 (2017) 73–92.
Kjellstrom, T., Kovats, R.S., Lloyd, S.J., Holt, T., Tol, R.S. 2009. The direct impact of climate change on regional labor productivity. Arch Environ Occup Health, 2009, 64(4), 217-27. https://doi.org/10.1080/19338240903352776

KJELLSTROM, T., LEMKE, B., OTTO, M., HYATT, O. & DEAR, K. 2014. Occupational Heat Stress: Contribution to WHO project on "Global assessment of the health impacts of climate change", Report. Mapua, New Zealand: Climate CHIP. Available at https://climatechip.org/sites/default/files/publications/TP2014_4_Occupational_Heat_Stress_WHO.pdf

Klein Tank, A. M. G., F. W. Zwiers, and X. Zhang (2009). Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation, Climate data and monitoring WCDMP-No. 72, WMO-TD No. 1500, 56 pp.

Kloster, S., Mahowald, N.M., Randerson J.T., Lawrence, P.J. (2012). The impacts of climate, land use, and demography on fires during the 21st century simulated by CLM-CN. Biogeosciences Discussions, 8(5), 9709–9746

Kloster, S., Mahowald, N.M., Randerson, J.T., Thornton, P.E., Hoffman, F.M., Levis, S., Lawrence, P.J., Feddema, J.J., Oleson, K.W., Lawrence, D.M. (2010). Fire dynamics during the 20th century simulated by the Community Land Model. Biogeosciences, 7, 1877–1902, 10 https://doi.org/10.5194/bg-7-1877-2010

Knobloch, F., Pollitt H., Chewpreecha U., Daioglou V. and Mercure J-F. (2018), "Simulating the deep decarbonisation of residential heating for limiting global warming to 1.5°C", Energy Efficiency, Volume 12, Issue 2, pp 521–550

Koks, E.E. (2019). DamageScanner (v0.3): Python tool for disaster damage assessments (Version v0.3)

Koks, E. E., & Haer, T. (2020). A high-resolution wind damage model for Europe. Scientific Reports, 10(1), 1-11.

Koks, E.E. & Haer T. (2020) A high-resolution wind damage model using OpenStreetMap. Nature Scientific Reports. In Review

Koks, E. E., Jongman, B., Husby, T. G., & Botzen, W. J. W. (2015). Combining hazard, exposure and social vulnerability to provide lessons for flood risk management. Environmental Science & Policy, 47, 42–52. https://doi.org/10.1016/j.envsci.2014.10.013

Koks, E.E., Rozenberg, J., Zorn, C., Tariverdi, M., Vousdoukas, M., Fraser, S.A., Hall, J.W. and Hallegatte, S., 2019. A global multi-hazard risk analysis of road and railway infrastructure assets. Nature communications, 10(1), p.2677.

Kontogianni, A., C.H. Tourkolias, D. Damigos and M. Skourtos (2013). Assessing sea-level-rise costs and adaptation benefits under uncertainty in Greece. Environmental Science & Policy. Vol 37: 61-78. http://dx.doi.org/10.1016/j.envsci.2013.08.006.

Kovats, R.S., Edwards, S., Hajat, S., Armstrong, B., Ebi, K.L., Menne, B. 2004. The effect of temperature on food poisoning: time series analysis in 10 European countries. Epidemiology and Infection, 132, 443-453.

Kovats, S, Lloyd, S, Hunt, A and Watkiss, P. (2011). Technical Policy Briefing Note 8: The Impacts and Economic Costs on Health in Europe and the Costs and Benefits of Adaptation, Results of the EC RTD ClimateCost Project. In Watkiss, P (Editor), 2011. The ClimateCost Project. Final Report. Volume 1: Europe. Published by the Stockholm Environment Institute, Sweden, 2011. ISBN 978-91-86125-35-6.

Kragt, M. E. (2009). A beginners guide to Bayesian network modelling for integrated catchment. Landscape Logic Technical Report No. 9, (9).

Kreibich, H., Thieken, A.H., Petrow, T., Müller, M. and Merz, B., 2005. Flood loss reduction of private households due to building precautionary measures--lessons learned from the Elbe flood in August 2002.

Kriegler E, Bertram C, Kuramochi T, Jakob M, Pehl M, Miodrag Stevanović, Höhne N, Luderer G, Minx JC, Fekete H, Hilaire J, Luna L, Alexander Popp, Steckel JC, Sterl S, Yalew AW, Dietrich JP, Edenhofer O (2018) Short term policies to keep the door open for Paris climate goals. Environmental Research Letters 13:074022

Kriegler, E., Edmonds, J., Hallegatte, S., Ebi, K., Kram, T., Riahi , K., Winkler, H., Van Vuuren, D.P., 2014. A new scenario framework for Climate Change Research: The concept of Shared Policy Assumptions. Clim Change 122, 401-414.

Kull, S.J., Rampley, G., Morken, S., Metsaranta, J., Neilson, E.T., & Kurz, W.A. (2016). Operational-scale Carbon Budget Model of the Canadian Forest Sector (CBM-CFS3) version 1.2: user’s guide. Nat. Resour. Can., Can. For. Serv., North. For. Cent., Edmonton, AB. https://cfs.nrcan.gc.ca/publications?id=36556

Kunreuther, H., Michel-Kerjan, E., Ranger, N. (2013). Insuring future climate catastrophes. Climatic Change, 118(2): 339-354.

Kurz, W.A., Dymond, C.C., White, T.M., Stinson, G., Shaw, C.H., Rampley, G.J., Smyth, C., Simpson, B.N., Neilson, E.T., Trofymow, J.A., Metsaranta, J., & Apps, M.J. (2009). CBM-CFS3: A model of carbon-dynamics in forestry and land-use change implementing IPCC standards. Ecol. Model., 220(4), 480-504.

Kwakkel, J., Jafino, B.A., Verbraeck, A., Eker, S., and Rozenberg, J. (2019). Resilience of the Transport Network in Bangladesh: A graph-theoretical and simulation-based approach (Washington DC: World Bank)

Kwasinski, A. 2013. Lessons from field damage assessments about communication networks power supply and infrastructure performance during natural disasters with a focus on Hurricane Sandy. In Proceedings of FCC Workshop on Network Resiliency 2013, 5 February 2013, New York, USA.

Kysely, J., & Picek, J. (2012, August 20). Charles University. Retrieved from School of mathematics:
http://www.karlin.mff.cuni.cz/~antoch/robust12/PREDNASKY/NEDELE/kysely.pdf

L., K. D. & G., D. R. Convolution Method for Time-Dependent Beach-Profile Response. J. Waterw. Port, Coastal, Ocean Eng. 119, 204–226 (1993)

Lacy, R. C. (1993). Vortex a computer simulation model for PVA.pdf (pp. 45–65). pp. 45–65.

Lam, V. W. Y., W. W. L. Cheung, G. Reygondeau, and U. Rashid Sumaila. 2016. Projected change in global fisheries revenues under climate change. Scientific Reports 6:1–8.
Lange, H.J. De, Sala, S., Vighi, M. and Faber, J.H. 2010. Ecological vulnerability in risk assessment — A review and perspectives. Science of the Total Environment. 408, pp.3871–3879.

Lassalle, G., P. Crouzet, J. Gessner, and E. Rochard. 2010. Global warming impacts and conservation responses for the critically endangered European Atlantic sturgeon. Biological Conservation 143:2441–2452.

Lavorel, S., Grigulis, K., Lamarque, P., Colace, M. P., Garden, D., Girel, J., … Douzet, R. (2011). Using plant functional traits to understand the landscape distribution of multiple ecosystem services. Journal of Ecology, 99(1), 135–147. https://doi.org/10.1111/j.1365-2745.2010.01753.x

Lawson, B. & Armitage, O. (2008). Weather guide for the Canadian Forest Fire Danger Rating System (84 p). Edmonton, Alberta: Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre

Lecca, P., Barbero, J., Christensen, M., Conte, A., Di Comite, F., Diaz-Lanchas, J., Diukanova, O., Mandras, G., Persyn, D. and Sakkas, S. (2018), "RHOMOLO V3: A Spatial Modelling Framework, EUR 29229 EN, Publications Office of the European Union, Luxembourg, 2018, ISBN 978-92-79-85886-4, doi:10.2760/671622, JRC111861.

Lee, H.-L., Hertel, T. W., Rose, S. and Tol, R. S. J.: Economic analysis of land use in global climate change policy, Routledge. [online] Available from: https://books.google.it/books?id=z16SAgAAQBAJ&pg=PA72&lpg=PA72&dq=Economic+analysis+of+land+use+in+global+climate+change+policy.+An+integrated+land+use+data+base+for+CGE+analysis+of+climate+policy+options&source=bl&ots=BH5hNYTAUb&sig=ACfU3U3r6oRhWp4fO9Agg (Accessed 21 February 2019), 2009.

Legendre, P., Legendre, L. (1998). Numerical Ecology (2nd ed). Amsterdam, Holland: Elsevier

Lehmann J., & Kleber, M. (2015). The contentious nature of soil organic matter. Nature, 528, 61-68.

Lehmann, P., Sijm, J., Gawel, E., Strunz, S., Chewpreecha, U., Mercure, J-F. and Pollitt, H, (2018), "Addressing multiple externalities from electricity generation: a case for EU renewable energy policy beyond 2020?", Environmental Economics and Policy Studies, Volume 21, Issue 2, pp 255–28

Lehsten, V., Tansey, K., Balzter, H., Thonicke, K., Spessa, A., Weber, U., Smith, B., Arneth, A. (2009). Estimating carbon emissions from African wildfires. Biogeosciences, 6, 349–360. https://doi.org/10.5194/bg-6-349-2009

Leichenko, R. M. and O'Brien, K. L.: The dynamics of rural vulnerability to global change: the case of southern Africa, Mitig. Adapt. Strat. Global Change, 7, 1–18, 2002.

Lemonsu, A., Viguié, V., Daniel, M., & Masson, V. (2015). Vulnerability to heat waves: Impact of urban expansion scenarios on urban heat island and heat stress in Paris (France). Urban Climate, 14, 586–605. https://doi.org/10.1016/j.uclim.2015.10.007

Lempert R.J. and Groves, D.G (2010). Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west. Technol. Forecast. Soc. 2010, 77, 960–974, doi:10.1016/j.techfore.2010.04.007.

Lempert, R. J. (2019). Robust decision making (RDM). In Decision Making under Deep Uncertainty (pp. 23-51): Springer.

Lempert, R. J., Popper, S. W., Groves, D. G., Kalra, N., Fischbach, J. R., Bankes, S. C., . . . Hackbarth, A. (2013). Making good decisions without predictions: Robust decision making for planning under deep uncertainty.

Lempert, R., Kalra, N., Peyraud, S., Mao, Z., Tan, S. B., Cira, D., & Lotsch, A. (2013). Ensuring robust flood risk management in Ho Chi Minh City: The World Bank.

Lenzen, M., Moran, D., Kanemoto, K., Geschke, A. (2013), "Building Eora: A Global Multi-regional Input-Output Database at High Country and Sector Resolution", Economic Systems Research, 25:1, 20-49, DOI:10.1080/09535314.2013.769938

Leonard, M., Westra, S., Phatak, A., Lambert, M., van den Hurk, B., Mcinnes, K., … Stafford-Smith, M. (2014). A compound event framework for understanding extreme impacts. Wiley Interdisciplinary Reviews: Climate Change, 5(1), 113–128. https://doi.org/10.1002/wcc.252

Lewis, O. T. (2006). Climate change, species-area curves and the extinction crisis. Philosophical Transactions of the Royal Society B: Biological Sciences, 361(1465), 163–171. https://doi.org/10.1098/rstb.2005.1712

Lewis, S. C., King, A. D., Perkins-Kirkpatrick, S. E., & Mitchell, D. M. (2019). Regional hotspots of temperature extremes under 1.5° C and 2° C of global mean warming. Weather and Climate Extremes, 26, 100233

Li, X., & Yeh, A. G. O. (2002). Neural-network-based cellular automata for simulating multiple land use changes using GIS. International Journal of Geographical Information Science, 16(4), 323–343. https://doi.org/10.1080/13658810210137004

Lin, N., & Chavas, D. (2012). On hurricane parametric wind and applications in storm surge modeling. Journal of Geophysical Research: Atmospheres, 117(D9).

Lincke, D., Hinkel, H., van Ginkel, K., Jeuken, A., Botzen, W., Tesselaar, M., Scoccimarro, E., & Ignjacevic, P. (2018). D2.3 Impacts on infrastructure, built environment, and transport. Deliverable of the H2020 COACCH Project.

Link, P. M., and Tol, R. S. J. (2011), "Estimation of the economic impact of temperature changes induced by a shutdown of the thermohaline circulation: An application of FUND", Climatic Change, 104(2)

Linkov, I. and Trump, B. D. (2019) The Science and Practice of Resilience. Cham: Springer International Publishing (Risk, Systems and Decisions). doi: 10.1007/978-3-030-04565-4.

Liu, J., Arndt, C. and T.W. Hertel (2004), "Parameter Estimation and Measures of Fit in A Global, General Equilibrium Model" Journal of Economic Integration, Vol. 19, No. 3, pp. 626-649

Lloyd-Hughes, B. (2014). The impracticality of a universal drought definition. Theoretical and Applied Climatology, 117, 607–611. https://doi.org/10.1007/s00704-013-1025-7

Loarie, S. R., Duffy, P. B., Hamilton, H., Asner, G. P., Field, C. B., & Ackerly, D. D. (2009). The velocity of climate change. Nature, 462(7276), 1052–1055. https://doi.org/10.1038/nature08649

Lobell, D. B., Hammer, G. L., McLean, G., Messina, C., Roberts, M. J., & Schlenker, W. (2013). The critical role of extreme heat for maize production in the United States. Nature Climate Change, 3(5), 497–501. https://doi.org/10.1038/nclimate1832

Lobell, D. B., Schlenker, W., & Costa-Roberts, J. (2011). Climate Trends and Global Crop Production Since 1980. Science, 333(6042), 616–620. https://doi.org/10.1126/science.1204531

Lobell, D., & Burke, M. (Eds.). (2010). Climate Change and Food Security (Vol. 37). Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-90-481-2953-9

Lofgren, H., Lee Harris, R., Robinson S. (2002), "A Standard Computable General Equilibrium (CGE) Model in GAMS", Microcomputers in Policy Research n.5, IFPRI.

Lokers, R., Knapen, R., Janssen, S., van Randen, Y., & Jansen, J. (2016). Analysis of Big Data technologies for use in agro-environmental science. Environmental Modelling and Software, 84, 494–504. https://doi.org/10.1016/j.envsoft.2016.07.017

López-Bernal, Á., Morales, A., García-Tejera, O., Testi, L., Orgaz, F., De Melo-Abreu, J. P., & Villalobos, F. J. (2018). OliveCan: A Process-Based Model of Development, Growth and Yield of Olive Orchards. Frontiers in Plant Science, 9. doi:10.3389/fpls.2018.00632

Lozano, O.M., Salis, M., Ager, A.A., Arca, B., Alcasena, F.J., Monteiro, A.T., Finney, M.A., Del Giudice, L., Scoccimarro, E. and Spano, D. (2017). Assessing Climate Change Impacts on Wildfire Exposure in Mediterranean Areas. Risk Analysis, 37, 1898-1916. https://doi.org/10.1111/risa.12739

Lucas, R. E. (1976). Econometric Policy Evaluation: A Critique. CarnegieRochester Conference Series on Public Policy, 1:19–46.

Luderer, G., Leimbach, M., Bauer, N., Kriegler, E., Baumstark, L., Bertram, C., Giannousakis, A., Hilaire, J., Klein, D., Levesque, A., Mouratiadou, I., Pehl, M., Pietzcker, R., Piontek, F. and Roming, N., Schultes, A., Schwanitz, V.J., Strefler, J. (2015) Description of the REMIND Model (Version 1.6) (November 30, 2015). Available at SSRN: https://ssrn.com/abstract=2697070 or http://dx.doi.org/10.2139/ssrn.2697070

Luers, A. L., Lobell, D. B., Sklar, L. S., Addams, C. L., and Matson, P. A.: A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico, Global Environ. Change, 13, 255–267, 2003

Luo, Y., Keenan, T.F., & Smith, M. (2015). Predictability of the terrestrial carbon cycle. Glob Chang Biology, 21, 1737–1751.

Lutz C, Meyer B, Wolter MI (2010), "The global multisector/multicountry 3-E model GINFORS. A description of the mode and a baseline forecast for global energy demand and CO2 emissions", International Journal of Global Environmental Issues, 10:25–45.

Luyssaert, S., Marie, G., Valade, A., Chen, Y. Y., Djomo, S. N., Ryder, J., *et al.* (2018). Trade-offs in using European forests to meet climate objectives. Nature 562, 259–262.

Lynch, A. J., S. J. Cooke, A. M. Deines, S. D. Bower, D. B. Bunnell, I. G. Cowx, V. M. Nguyen, J. Nohner, K. Phouthavong, B. Riley, M. W. Rogers, W. W. Taylor, W. Woelmer, S. J. Youn, and T. D. Beard. 2016. The social, economic, and environmental importance of inland fish and fisheries. Environmental Reviews 24:115–121.

Lytle, D. A., and N. L. Poff, 2004: Adaptation to natural flow regimes. Trends Ecol. Evol., 19, 94–100, https:// doi.org/10.1016/j.tree.2003.10.002.

MacDonald, G. M., Bennett, K. D., Jackson, S. T., Parducci, L., Smith, F. A., Smol, J. P., & Willis, K. J. (2008). Impacts of climate change on species, populations and communities: palaeobiogeographical insights and frontiers. Progress in Physical Geography, 32(2), 139–172. https://doi.org/10.1177/0309133308094081

Macgregor, N. A., and N. van Dijk. 2014. Adaptation in Practice: How Managers of Nature Conservation Areas in Eastern England are Responding to Climate Change. Environmental Management 54:700–719.

Mach, K. J., Planton, S. and von Stechow, C. (2014) 'IPCC, 2014: Annex II: Glossary', Cli- mate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC).

Maidment, D. R. (1993). Handbook of hydrology. New York: McGraw–Hill.

Maisey, P., Becker, B., Steptoe, H. 2017. WISC Storm Footprint (Gridded Windfield) Description. Copernicus Climate Change Service

Mallampalli, V.R., Mavrommati, G., Thompson, J., Duveneck, M., Meyer, S., Ligmann-Zielinska, A., Druschke, C.G., Hychka, K., Kenney, M.A., Kok, K., Borsuk, M.E., 2016. Methods for translating narrative scenarios into quantitative assessments of land use change. Environmental Modelling & Software 82, 7-20.

Mallinis, G., Mitsopoulos, I., Dimitrakopoulos, A., Gitas, I., Karteris M.,(2008). Integration of local scale fuel type mapping and fire behaviour prediction using high spatial resolution imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 4, 230-238

Manne, A.S. and S. Gunter, (2005), "Global climate change and the equity–efficiency puzzle", Energy, Elsevier, vol. 30(14), 2525-2536.

Marcot, B. G., J. D. Steventon, G. D. Sutherland, and R. K. McCann. 2006. Guidelines for developing and updating Bayesian belief networks applied to ecological modeling and conservation. Canadian Journal of Forest Research 36:3063–3074.

Marin-Ferrer, M., Vernaccini, L. and Poljansek, K. (2017) Index for Risk Management - INFORM. Concept and Methodology. Luxembourg.

Markandya, A., De Cian, E., Drouet, L., Polanco-Martinez, J and F. Bosello (2019), "Building Risk into the Mitigation/Adaptation Decisions simulated by Integrated Assessment Models", Environmental and Resource Economics (2019) 74:1687–1721

Markstrom, S.L., Niswonger, R.G., Regan, R.S., Prudic, D.E., and Barlow, P.M. (2008): GSFLOW-Coupled Ground-water and Surface-water FLOW model based on the integration of the Precipitation-Runoff Modeling System (PRMS) and the Modular Ground-Water Flow Model (MODFLOW-2005): U.S. Geological Survey Techniques and Methods 6-D1, 240 p.

Marzi, S. *et al.* (2019) 'Constructing a comprehensive disaster resilience index: The case of Italy', PLoS ONE. Public Library of Science, 14(9). doi: 10.1371/journal.pone.0221585.

Marzi, S., Mysiak, J. and Santato, S. (2018) 'Comparing adaptive capacity index across scales: The case of Italy', Journal of Environmental Management. Academic Press, 223, pp. 1023–1036. doi: 10.1016/j.jenvman.2018.06.060.

Masson, V., Marchadier, C., Adolphe, L., Aguejdad, R., Avner, P., Bonhomme, M., … Zibouche, K. (2014). Adapting cities to climate change: A systemic modelling approach. Urban Climate, 10(P2), 407–429. https://doi.org/10.1016/j.uclim.2014.03.004

Maxwell, S. L., Venter, O., Jones, K. R., & Watson, J. E. M. (2015). Integrating human responses to climate change into conservation vulnerability assessments and adaptation planning. Annals of the New York Academy of Sciences, 1355(1), 98–116. https://doi.org/10.1111/nyas.12952

McCallum, S., Dworak, T., Prutsch, A., Kent, N., Mysiak, J., Bosello, F., Klostermann, J., Dlugolecki, A., Williams, E., König, M., Leitner, M., Miller, K., Harley, M., Smithers, R., Berglund, M., Glas, N., Romanovska, L., van de Sandt, K., Bachschmidt, R., Völler, S., Horrocks, L. (2013). Support to the development of the EU Strategy for Adaptation to Climate Change: Background report to the Impact Assessment, Part I – Problem definition, policy context and assessment of policy options. Environment Agency Austria, Vienna.

McConochie, J. D., Hardy, T. A., & Mason, L. B. (2004). Modelling tropical cyclone over-water wind and pressure fields. Ocean engineering, 31(14-15), 1757-1782.

McCormick, S., (2010). Hot or not? Obstacles to the emergence of climate-induced illness movements. In: Social Movements and Health Care in the United States. Zald, M., J. Banaszak-Holl, and S. Levitsky (eds.). Oxford University Press, Oxford, UK.

McIlgorm, A., Hanna, S., Knapp, G., Le Floc'H, P., Millerd, F., & Pan, M. (2010). How will climate change alter fishery governance{glottal stop} Insights from seven international case studies. Marine Policy, 34(1), 170–177. https://doi.org/10.1016/j.marpol.2009.06.004

McMahon, S. M., Harrison, S. P., Armbruster, W. S., Bartlein, P. J., Beale, C. M., Edwards, M. E., … Prentice, I. C. (2011). Improving assessment and modelling of climate change impacts on global terrestrial biodiversity. Trends in Ecology and Evolution, 26(5), 249–259. https://doi.org/10.1016/j.tree.2011.02.012

McSweeney, C. F., & Jones, R. G. (2016). How representative is the spread of climate projections from the 5 CMIP5 GCMs used in ISI-MIP?. Climate Services, 1, 24-29.

Mechler R, Czajkowski J, Kunreuther H, Michel-Kerjan E, Botzen W, Keating A, McQuistan C, Cooper N, *et al.* 2014. Making Communities More Flood Resilient: The Role of Cost Benefit Analysis and Other Decision-support Tools in Disaster Risk Reduction. White Paper, Zurich Flood Resilience Alliance

Mechler, R. and Islam, N. 2013. Cost Benefit Analysis of Disaster Risk reduction and Climate Adaptation in Bangladesh. In: D. Guha-Sapir and I. Santos. The Economic Impacts of Natural Disasters. Assessing the Costs of Prevention, Mitigation and Adaptation. Cambridge University.

Meehl, G. A., and C. Tebaldi (2004), More intense, more frequent and longer lasting heat waves in the 21st century, Science, 305, 994– 997

Meehl, G.A., T.F. Stocker, W.D. Collins, P. Friedlingstein, A.T. Gaye, J.M. Gregory, A. Kitoh, R. Knutti, J.M. Murphy, A. Noda, S.C.B. Raper, I.G. Watterson, A.J. Weaver and Z.-C. Zhao, 2007: Global Climate Projections. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [Solomon, S., D. Qin, M. Manning, Z. Chen, M. Marquis, K.B. Averyt, M. Tignor and H.L. Miller (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. (www.ipcc.ch).

Mehran, A., O. Mazdiyasni, and A. AghaKouchak (2015): A hybrid framework for assessing socioeconomic drought: Linking climate variability, local resilience, and demand, J. Geophys. Res. Atmos., 120, doi:10.1002/2015JD023147.

Melitz, M.J. (2003), "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity", Econometrica, Econometric Society, vol. 71(6), pages 1695-1725, November.

Mendizabal, E. 2007. The Alignment , Interest and Influence Matrix (AIIM). , pp.1–6.

Mendoza, G., Jeuken, A., Matthews, J. H., Stakhiv, E., Kucharski, J., & Gilroy, K. (2018). Climate Risk Informed Decision Analysis (CRIDA): collaborative water resources planning for an uncertain future: UNESCO Publishing.

Mereu V. *et al.* (2018) Robust Decision Making for a Climate-Resilient Development of the Agricultural Sector in Nigeria. In: Lipper L., McCarthy N., Zilberman D., Asfaw S., Branca G. (eds) Climate Smart Agriculture. Natural Resource Management and Policy, vol 52. Springer, Cham – doe it do costs?
https://link.springer.com/chapter/10.1007/978-3-319-61194-5_13

Mereu, Gallo, & Spano. (2019). Optimizing Genetic Parameters of CSM-CERES Wheat and CSM-CERES Maize for Durum Wheat, Common Wheat, and Maize in Italy. Agronomy, 9(10), 665. https://doi.org/10.3390/agronomy9100665

Metherell, A.K., Harding, L.A. , Cole, C.V., Parton, W.J. (1993) CENTURY Soil Organic Matter Model Environment: Technical Documentation v4.0

Metzger, M.J., Rounsevell, M.D.A. and Acosta-michlik, L. 2006. The vulnerability of ecosystem services to land use change. . 114, pp.69–85.

Meyer, V., Becker, N., Markantonis, V., Schwarze, R., Van Den Bergh, J., Bouwer, L., Bubeck, P., Ciavola, P., Genovese, E., Green, C.H. and Hallegate, S., 2013. Assessing the costs of natural hazards-state of the art and knowledge gaps. Natural Hazards and Earth System Sciences, 13(5), pp.1351-1373.

MIECZKOWSKI, Z. (1985). THE TOURISM CLIMATIC INDEX: A METHOD OF EVALUATING WORLD CLIMATES FOR TOURISM. The Canadian Geographer/Le Géographe Canadien, 29(3), 220–233. https://doi.org/10.1111/j.1541-0064.1985.tb00365.x

Migliavacca, M., Dosio, A., Camia, A., Hobourg, R., Houston-Durrant, T., Kaiser, J.K., Khabarov N., Krasovskii, A.A., Marcolla B., San Miguel-Ayanz, J.,Ward, D.S., Cescatti, A. (2013a). Modeling biomass burning and related carbon emissions during the 21st century in Europe. Journal of Geophysical Research and Biogeoscience, 118, 1732–1747. https://doi.org/10.1002/2013JG002444.

Migliavacca, M., Dosio, A., Kloster, S., Ward, D.S., Camia, A., Houborg, R., Houston Durrant, T., Khabarov, N., Krasovskii, A.A., San Miguel–Ayanz, J., Cescatti, A. (2013b). Modeling burned area in Europe with the community land model. Journal of Geophysical Research and Biogeoscience, 118(1), 265–279. https://doi.org/10.1002/jgrg.20026

Miller, K., F. Huettmann, B. Norcross, and M. Lorenz. 2014. Multivariate random forest models of estuarine-associated fish and invertebrate communities. Marine Ecology Progress Series 500:159–174.

Millner A, Dietz S, Heal G (2013), "Scientific Ambiguity and Climate Policy". Environment and Resource Economics 55:21–46

Mishra AK, Singh VP (2010) A review of drought concepts. Journal of Hydrology 391 202-216

Mishra AK, Singh VP (2011) Drought modelling - a review. Journal of Hydrology 403 157–175

Mishra, A K. Sivakumar, B S, Vijay P. 2015 Drought processes, modeling, and mitigation. Editorial in Journal of Hydrology vol 526 1-2.

Mitchell, R.K. and Wood, D.J. 1997. Toward a Theory of Stakeholder Identification and Salience : Defining the Principle of Who and What Really Counts Author (s): Ronald K . Mitchell , Bradley R . Agle and Donna J . Wood Source : The Academy of Management Review , Vol . 22 , No . 4 (Oct . . 22(4), pp.853–886.

Mitsopoulos, I., Mallinis, G., Karali, A., Giannakopoulos, C., Arianoutsou, M. (2016). Mapping fire behaviour under changing climate in a Mediterranean landscape in Greece. Regional Environmental Change,16, 1929–1940. https://doi.org/10.1007/s10113-015-0884-0

Mokany, K., & Ferrier, S. (2011). Predicting impacts of climate change on biodiversity: A role for semi-mechanistic community-level modelling. Diversity and Distributions, 17(2), 374–380. https://doi.org/10.1111/j.1472-4642.2010.00735.x

Mol, J.M., Botzen, W.J.W., Blasch, J.E. (2018). Behavioral motivations for self-insurance under different disaster risk insurance schemes. Journal of Economic Behavior & Organization https://doi.org/10.1016/j.jebo.2018.12.007

Mol, J.M., Botzen, W.J.W., Blasch, J. (2020). Risk reduction in natural disaster insurance: Experimental evidence on moral hazard and financial incentives. Journal of Behavioral and Experimental Economics, 84: 101500. 10.1016/j.socec.2019.02.007

Molinari, D., de Bruijn, K. M., Castillo-Rodríguez, J. T., Aronica, G. T., & Bouwer, L. M. (2019). Validation of flood risk models: Current practice and possible improvements. International Journal of Disaster Risk Reduction, 33, 441–448. https://doi.org/https://doi.org/10.1016/j.ijdrr.2018.10.022

Mönkkönen, M., Juutinen, A., Mazziotta, A., Miettinen, K., Podkopaev, D., Reunanen, P., *et al.* (2014). Spatially dynamic forest management to sustain biodiversity and economic returns. Journal Environmental Management, 134, 80–89.

Montoro Girona, M., Rossi, S., Lussier, J.-M., Walsh, D., and Morin, H. (2017). Understanding tree growth responses after partial cuttings: a new approach. PLoS One, 12:e0172653.

Mora, C., Metzger, R., Rollo, A., & Myers, R. A. (2007). Experimental simulations about the effects of overexploitation and habitat fragmentation on populations facing environmental warming. Proceedings of the Royal Society B: Biological Sciences, 274(1613), 1023–1028. https://doi.org/10.1098/rspb.2006.0338

Moriasi, D., Arnold, J., Van Liew, M., Bingner, R., Harmel, R., & Veith, T. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans. ASABE, 50(3), 885-900.

Mubareka, S., Vacchiano, G., Pilli, R., Hilferink, M., & Fiorese G. (2018). Integrated modelling approach to assess woody biomass supply demand and environmental impacts of forest management in the EU. iEMSs 9th International Congress on Environmental Modelling and Tools.

Multicriteria Analysis (MCA). Retrieved 16 January 2020, from https://unfccc.int/files/adaptation/methodologies_for/vulnerability_and_adaptation/application/pdf/multicriteria_analysis__mca_pdf.pdf

Mungkasi, S., & Roberts, S. G. (2011). A finite volume method for shallow water flows on triangular computational grids. Advanced Computer Science and Information System (ICACSIS), 2011 International Conference on Advanced Computer Science and Information Systems, M(4), 79–84.

Murakami, D., Yamagata, Y., 2016. Estimation of gridded population and GDP scenarios with spatially explicit statistical downscaling. https://arxiv.org/ftp/arxiv/papers/1610/1610.09041.pdf.

Murdock, H. J., De Bruijn, K. M., & Gersonius, B. (2018). Assessment of critical infrastructure resilience to flooding using a response curve approach. Sustainability, 10(10), 3470

Murphy, P.B., Williamson, D.J., Bowman, D.M.J.S. (2011). Fire regimes: Moving from a fuzzy concept to geographic entity. New Phytologist, 192(2), 316–318

Mysiak, J. *et al.* (2018) 'Climate risk index for Italy', Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376(2121). doi: 10.1098/rsta.2017.0305.

Mysiak, J., Torresan, S., Bosello, F., Mistry, M., Amadio, M., Marzi, S., ... & Sperotto, A. (2018). Climate risk index for Italy. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376(2121), 20170305.

Nakicenovic, N. Alcamo, J., Davis, G., de Vries, B., Fenhann, J., Gaffin, S., Gregory, K., Griibler, A., Jung, T.J., Kram, T., Lebre La Rovere, E., Michaelis, L., Mori, S., Morita, T., Pepper, W., Pitcher, H., Price, L., Riahi, K., Roehrl, A., Rogner, H-H, Sankovski, A., Schlesinger, M., Shukla, P., Smith, S., Swart, R., van Rooijen, S., Victor, N., Dadi Z (2000), "Special Report on Emissions Scenarios", A Special Report of Working Group III of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge

Nassopoulos, H., Dumas, P., & Hallegatte, S. (2012). Adaptation to an uncertain climate change: cost benefit analysis and robust decision making for dam dimensioning. Climatic change, 114(3-4), 497-508. doi:10.1007/s10584-012-0423-7

Nastos, P. T., Papadimou, K. K., & Matsangouras, I. T. (2018). Mediterranean tropical-like cyclones: Impacts and composite daily means and anomalies of synoptic patterns. Atmospheric Research, 208, 156-166.

Naumann, G., P. Barbosa, L. Garrote, A. Iglesias, and J. Vogt. 2014. "Exploring Drought Vulnerability in Africa: An Indicator Based Analysis to Be Used in Early Warning Systems." Hydrol. Earth Syst. Sci. 18: 1591–604. https://doi.org/10.5194/hess-18-1591-2014.

Neitsch, S. L., Arnold, J. G., Kiniry, J. R., & Williams, J. R. (2011). Soil and Water Assessment Tool. Theoretical Documentation. Version 2009. In Texas Water Resources Institute Technical Report No. 406. https://doi.org/10.1016/j.scitotenv.2015.11.063

Nelson, D. R., Adger, W. N., & Brown, K. (2007). Adaptation to environmental change: contributions of a resilience framework. Annu. Rev. Environ. Resour., 32, 395–419.

Niemelä, R., Hannula, M., Rautio, S., Reijula, K., & Railio, J. (2002). The effect of air temperature on labour productivity in call centres - A case study. Energy and Buildings, 34(8), 759–764. https://doi.org/10.1016/S0378-7788(02)00094-4

Noble, I.R., Bary, G.A.V., Gill, A.M. (1980). McArthur's fire-danger meters expressed as equations. Australian Journal of Ecology, 5, 201-203. https://doi.org/10.1111/j.1442-9993.1980.tb01243.x

Nobre, A. M., Ferreira, J. G., Nunes, J. P., Yan, X., Bricker, S., Corner, R., … Zhu, M. (2010). Assessment of coastal management options by means of multilayered ecosystem models. Estuarine, Coastal and Shelf Science, 87(1), 43–62. https://doi.org/10.1016/j.ecss.2009.12.013

Nordhaus, W.D. (2017), "Revisiting the social cost of carbon", PNAS February 14, 2017 114 (7) 1518-1523

Nordhaus, W. D. and Yang, Z. (1996). "A Regional Dynamic General-Equilibrium Model of Alternative Climate-Change Strategies", American Economic Review, 86 (4), pp. 741–765.

Nord-Larsen, T., & Johannsen, V.K. (2007). A statespace approach to stand growth modelling of European beech. Ann For Sci, 64(4), 365-374.

OECD (2008) 'Handbook on constructing composite indicators', OECD publications. Paris. Available at: http://www.oecd-ilibrary.org/economics/handbook-on-constructing-composite-indicators_533411815016 (Accessed: 11 May 2016).
OECD. (2014). Guidelines for resilience systems analysis.

Oh, J.E., Espinet Alegre, X., Pant, R., Koks, E.E., Russell, T., Schoenmakers, R. and Hall, J.W., 2019. Addressing Climate Change in Transport: Volume 2: Pathway to Resilient Transport.

Oleson, K. W., Bonan, G. B., & Feddema, J. (2010). Effects of white roofs on urban temperature in a global climate model. Geophysical Research Letters, 37(3). https://doi.org/10.1029/2009GL042194

O'Neill, B.C., Kriegler, E., Riahi, K., Ebi, K.L., Hallegatte, S., Carter, T.R., Mathur, R., van Vuuren, D.P., 2014. A new scenario framework for climate change research: The concept of shared socioeconomic pathways. Clim Change 122, 387-400.

Ostfeld R S. and Brunner J L. (2015). Climate change and Ixodes tick-borne diseases of humans370Phil. Trans. R. Soc. B.http://doi.org/10.1098/rstb.2014.0051

Ouyang, M. 2014. Review on modeling and simulation of interdependent critical infrastructure systems. Reliability Engineering & System Safety 121: 43–60.

Owen, P.R. (1964). Saltation of uniform grains in air. J. Fluid Mech., 20, 225-242.

Oxford Sustainable Finance Programme. (2018). Climate risk analysis from space : remote sensing, machine learning, and the future of measuring climate-related risk, (July).

Oyafuso, Z. S., Drazen, J. C., Moore, C. H., & Franklin, E. C. (2017). Habitat-based species distribution modelling of the Hawaiian deepwater snapper-grouper complex. Fisheries Research, 195(June), 19–27. https://doi.org/10.1016/j.fishres.2017.06.011

Paci, D. (2014). Human Health Impacts of Climate change in Europe. Report for the PESETA II project. JRC Technical Reports, Report EUR 26494EN.

Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., et al (2011). A large and persistent carbon sink in the world's forests. Science 333, 988–993.

Pant, R., J.W. Hall, and S.P. Blainey. 2016. Vulnerability assessment framework for interdependent critical infrastructures: Case-study for Great Britain's rail network. European Journal of Transport and Infrastructure Research 16(1): 174–194.

Pant, R., Koks, E.E., Russell, T., Hall, J.W., 2018. Transport Risks Analysis for The United Republic of Tanzania – Systemic vulnerability assessment of multi-modal transport networks. 10.13140/RG.2.2.25497.26722.

Pant, R., S. Thacker, J.W. Hall, D. Alderson, and S. Barr. 2017. Critical infrastructure impact assessment due to flood exposure. Journal of Flood Risk Management 11(1): 22–33.

Paprotny, D, Morales-Nápoles, O, Vousdoukas, MI, Jonkman, SN, Nikulin, G. Accuracy of pan-European coastal flood mapping. J Flood Risk Management. 2019; 12:e12459. https://doi.org/10.1111/jfr3.12459

Parton, W. J., Scurlock, J. M. O., Ojima, D. S., Gilmanov, T. G., Scholes, R. J., Schimel, D. S., Kirchner, T., Menaut, J-C., Seastedt, T., Garcia Moya E., Apinan Kamnalrut, & Kinyamario J. I. (1993). Observations and modeling of biomass and soil organic matter dynamics for the grassland biome worldwide. Global Biogeochem. Cycles, 7(4), 785– 809.

Pasini, S., Torresan, S., Rizzi, J., Zabeo, A., Critto, A., & Marcomini, A. (2012). Climate change impact assessment in Veneto and Friuli Plain groundwater. Part II: a spatially resolved regional risk assessment. The Science of the Total Environment, 440, 219–235. https://doi.org/10.1016/j.scitotenv.2012.06.096

Pasqui, M., & Di Giuseppe, E. (2019). Climate change, future warming, and adaptation in Europe. Animal Frontiers, 9(1), 6-11

Patt, A. and Siebenhüner, B.: Agent-based Modeling and Adaptation to Climate Change, Vierteljahrshefte zur Wirtschaftsforsch., 74(2), 310–320, doi:10.3790/vjh.74.2.310, 2005.

Paudel, Y., Botzen, W.J.W., Aerts, J.C.J.H. (2015a). Influence of climate change scenarios on catastrophe insurance: A case study of flood risk in the Netherlands. Regional Environmental Change, 8(2): 116-134.

Paudel, Y., Botzen, W.J.W., Aerts, J.C.J.H., Dijkstra, T.K. (2015b). Risk allocation in a public-private catastrophe insurance system: an actuarial analysis of deductibles, stop-loss, and premiums. Journal of Flood Risk Management, 8: 116-134.

Pearl, J. (1988). Probabilistic reasoning in intelligent systems: Networks of plausible inference. Morgan Kauffmann Publishers Inc.

Pederson, G. T., S. T. Gray, D. B. Fagre, and J. Graumlich, 2006: Long-duration drought variability and impacts on ecosystem services: A case study from Glacier National Park, Montana. Earth Interact., 10, https:// doi.org/10.1175/EI153.1.

Pereira, H. M., Leadley, P. W., Proença, V., Alkemade, R., Scharlemann, J. P. W., Fernandez-Manjarrés, J. F., … Walpole, M. (2010). Scenarios for global biodiversity in the 21st century. Science, 330(6010), 1496–1501. https://doi.org/10.1126/science.1196624

Pérez-Sánchez, J., Senent-Aparicio, J., Díaz-Palmero, J.M., Cabezas-Cerezo, J.D. (2017). A comparative study of fire weather indices in a semiarid south-eastern Europe region. Case of study: Murcia (Spain). Science of the Total Environment, 590(1),761-74. https://doi.org/10.1016/j.scitotenv.2017.03.040

Perkins, S.E. (2015). A review on the scientific understanding of heatwaves. Their measurement, driving mechanisms, and changes at the global scale. Atmospheric Research, 164, 242–267

Peterson, A. T. (2006). Uses and Requirements of Ecological Niche Models and Related Distributional Models. Biodiversity Informatics, 3(0), 59–72. https://doi.org/10.17161/bi.v3i0.29ses and Requirements of Ecological Niche Models and Related Distribution. Biodiversity Informatics, 3(0), 59–72. https://doi.org/10.17161/bi.v3i0.29

Pfahl, S., O'Gorman, P. & Fischer, E. (2017). Understanding the regional pattern of projected future changes in extreme precipitation. Nature Climate Change, 7, 423–427 Pfeiffer, M. & Kaplan, J.O. (2012). SPITFIRE- 2: An improved fire module for Dynamic Global Vegetation Models. Geoscientific Model Development Discussions, 5(3), 2347-2443. https:// doi.org/10.5194/gmdd-5-2347-2012.

Phakamas, N., Jintrawet, A., Patanothai, A., Sringam, P., & Hoogenboom, G. (2013). Estimation of solar radiation based on air temperature and application with the DSSAT v4.5 peanut and rice simulation models in Thailand. Agricultural and Forest Meteorology, 180, 182–193. https://doi.org/10.1016/j.agrformet.2013.06.015

Pindyck, R.S. (2013), "Climate Change Policy: What Do the Models Tell Us?", Journal of Economic Literature, American Economic Association, vol. 51(3), pages 860-72,

Pinnegar, J. K., and N. V. C. Polunin. 2004. Predicting indirect effects of fishing in Mediterranean rocky littoral communities using a dynamic simulation model. Ecological Modelling 172:249–267.

Poch, M., Comas, J., Rodríguez-Roda, I., Sanchez-Marre, M., & Cortés, U. (2004). Designing and building real environmental decision support systems. Environmental Modelling & Software, 19(9), 857–873.

Poeplau, C., Don, A., Vesterdal, L., Leifeld, J., Van Wesemael, B., Schumacher, J., & Gensior, A (2011). Temporal dynamics of soil organic carbon after land-use change in the temperate zone—carbon response functions as a model approach. Global Change Biology, 17(7), 2415–2427.

Pollitt, H. and Barker, T. (2009),"Modelling the Financial Crisis with the Global E3MG Model", IUP Journal of Applied Economics, 8 (5-6): 5-31.

Polsky, C., Neff, R., & Yarnal, B. (2007). Building comparable global change vulnerability assessments: The vulnerability scoping diagram. Global Environmental Change, 17(3–4), 472–485. https://doi.org/10.1016/j.gloenvcha.2007.01.005

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B.L., Dietrich, J.P., Doelmann, J.C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., Kriegler, E., Lotze-Campen, H., Fricko, O., Riahi, K., Vuuren, D.P.V., 2017. Land-use futures in the shared socio-economic pathways. Glob Environ Change 42, 331-345.

Popp, A., Humpenöder, F., Weindl, I., Bodirsky, B., Bonsch, M., Lotze-Campen, H., Müller, C., Biewald, A., Rolinski, S., Stevanovic, M., & Dietrich, J.P. (2014). Land-use protection for climate change mitigation. Nature Climate Change, 4: 1095–1098.

Popp, D. (2006), "ENTICE-BR: The Effects Of Backstop Technology R&D On Climate Policy Models," Energy Economics, v28(2,Mar), 188-202.

Porthin, M., Rosqvist, T., Perrels, A., & Molarius, R. (2013). Multi-criteria decision analysis in adaptation decision-making: a flood case study in Finland. Regional Environmental Change, 13(6), 1171-1180.

Poussin, J., Botzen, W.J.W., Aerts, J.C.J.H. (2014). Factors of influence on flood damage mitigation behaviour by households - Literature review and results from a French survey. Environmental Science and Policy, 40: 69-77.

Preece, R. M., & Jones, H. A. (2002). The effect of Keepit Dam on the temperature regime of the Namoi River, Australia. River Research and Applications, 18(4), 397–414. https://doi.org/10.1002/rra.686

Prentice, I.C., Kelley, D.I., Foster, P.N., Friedlingstein, P., Harrison, S.P., Bartlein, P.J. (2011). Modeling fire and the terrestrial carbon balance. Global Biogeochemical Cycles, 25(3), GB3005.

Preston, B.L., Yuen, E.J. and Westaway, R.M. 2011. Putting vulnerability to climate change on the map: a review of approaches, benefits, and risks. Sustainability science. 6(2), pp.177–202.

Pretzsch, H. (2009). Forest dynamics, growth and yield. Berlin Heidelberg: Springer-Verlag.

Prinn, R., Jacoby, H., Sokolov, A., Wang, C., Xiao, X., Yang, Z., Eckaus, R., Stone, P., Ellerman, D., Melillo, J., Fitzmaurice, J., Kicklighter, D., Holian, G., and Liu, Y. (1999). "Integrated Global System Model for Climate Policy Assessment: Feedbacks and Sensitivity Studies", Climatic Change, 41 (3/4), pp. 469–546.

PROMETHEE. (2011). Retrieved 5 January 2020, from http://www.promethee-gaia.net/promethee.html

Pukkala, T. (2018). Effect of species composition on ecosystem services in European boreal forest. Journal Forestry Reseqarch, 29, 261–272.

Pytharoulis I., Matsangouras I.T., Tegoulias I., Kotsopoulos S., Karacostas T.S., Nastos P.T. (2017) Numerical Study of the Medicane of November 2014. In: Karacostas T., Bais A., Nastos P. (eds) Perspectives on Atmospheric Sciences. Springer Atmospheric Sciences.

Rabin, S.S., Melton, J.R., Lasslop, G., Bachelet, D., Forrest, M., Hantson, S., Kaplan, J.O., Li, F., Mangeon, S., Ward, D.S., Yue, C., Arora, V.K., Hickler, T., Kloster, S., Knorr, W., Nieradzik, L., Spessa, A., Folberth, G. A., Sheehan, T., Voulgarakis, A., Kelley, D. I., Prentice, I. C., Sitch, S., Harrison, S., Arneth, A. (2017). The Fire Modeling Intercomparison Project (FireMIP), phase 1: experimental and analytical protocols with detailed model descriptions. Geoscientific Model Development, 10, 1175–1197. https://doi.org/10.5194/gmd-10-1175-2017, 2017.

Ramieri, E., Hartley, A., Barbanti, A., Santos, F. D., Gomes, A., Hilden, M., … Santini, M. (2011). Methods for assessing coastal vulnerability to climate change. ETC CCA Technical Paper, 1(2011), 1–93.

Ramirez, J., Monedero, S., Buckley, D. (2011). New approaches in fire simulations analysis with Wildfire Analyst. https://doi.org/10.13140/2.1.2045.7766.

Ranasinghe, R. & Stive, M.J.F. Climatic Change (2009). Rising seas and retreating coastlines 97: 465. https://doi.org/10.1007/s10584-009-9593-3

Ranasinghe, R., Callaghan, D. & Stive, M. J. F. Estimating coastal recession due to sea level rise: beyond the Bruun rule. Clim. Change 110, 561–574 (2012)

Rastall, M. (2018). Decision Support Methods for Climate Change Adaptation 6 - Multi Citeria Analysis. Retrieved 10 December 2019, from https://www.weadapt.org/sites/weadapt.org/files/legacy-new/knowledge-base/files/742/526a3d410cd11decision-support-methods-for-climate-change-adaptation-6-multi-criteria-analysis-summary-of-methods-and-case-study-examples-from-the-mediation-project.pdf

Rauff, O. K., & Bello, R. (2015). A Review of Crop Growth Simulation Models as Tools for Agricultural Meteorology. Agricultural Sciences, 06(09), 1098–1105. https://doi.org/10.4236/as.2015.69105

Ray, P. A., & Brown, C. M. (2015). Confronting climate uncertainty in water resources planning and project design: The decision tree framework: The World Bank.

Razavi, T., Switzman, H., Arain, A., & Coulibaly, P. (2016). Regional climate change trends and uncertainty analysis using extreme indices: A case study of Hamilton, Canada. Climate Risk Management, 13, 43-63.

Stephenson, D. B., Diaz, H. F., & Murnane, R. J. (2008). Definition, diagnosis, and origin of extreme weather and climate events. Climate Extremes and Society, 340, 11-23.

Reed, J. M., Mills, L. S., Dunning, J. B., Menges, E. S., McKelvey, K. S., Frye, R., … Miller, P. (2002). Emerging issues in population viability analysis. Conservation Biology, 16(1), 7–19. https://doi.org/10.1046/j.1523-1739.2002.99419.x

Reed, M.S., Graves, A., Dandy, N., Posthumus, H., Hubacek, K., Morris, J., Prell, C., Quinn, C.H. and Stringer, L.C. 2009. Who's in and why? A typology of stakeholder analysis methods for natural resource management. Journal of Environmental Management. 90(5), pp.1933–1949.

Reeder, T., & Ranger, N. (2011). How do you adapt in an uncertain world?: lessons from the Thames Estuary 2100 project

Reich, B. (2016, July 26). North Carolina State University. Retrieved from Department of Statistics: https://www4.stat.ncsu.edu/~reich/talks/Rossby.pdf

Reichstein, M., Bahn, M., Ciais, P., Frank, D., Mahecha, M.D., Seneviratne, S.I., Zscheischler, J., Beer, C., Buchmann, N., Frank, D.C., Papale, D., Rammig, A., Smith, P., Thonicke, K., van der Velde, M., Vicca, S., Walz, A., & Wattenbach, M. (2013). Climate extremes and the carbon cycle. Nature, 500, 287–295.

Reilly, J., Hohmann, N. and Kane, S.: Climate change and agricultural trade: Who benefits, who loses?, Glob. Environ. Chang., 4(1), 24–36, doi:10.1016/0959-3780(94)90019-1, 1994.

RESIN (2018) European Climate Risk Typology, European Commission. Available at: http://european-crt.org/map.html (Accessed: 3 December 2018).

Riahi, K., Kriegler, E., Johnson,N., Bertram, C, den Elzen, M., Eom, J., Schaeffer, M., Edmonds, J., Isaac, M., Krey, V., Longden,T., Luderer, G., Méjean, A., McCollum, D. L., Mima,. S., Turton, H., van Vuuren,D.P., Wada, K., Bosetti,V., Capros,P., Criqui,P., Hamdi-Cherif,M., Kainuma,M., Edenhofer O. (2015), "Locked into Copenhagen pledges - Implications of short-term emission targets for the cost and feasibility of long-term climate goals", Technological Forecasting and Social Change, 0(PA), pp. 8-23,

Riahi, K., van Vuuren, D.P., Kriegler, E., Edmonds, J., O'Neill, B.C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J.C., KC, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L.A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J.C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A., Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. Global Environmental Change, 42: 237-250.

Rianna, G., Reder, A., Mercogliano, P., & Pagano, L. (2017). Evaluation of variations in frequency of landslide events affecting pyroclastic covers in Campania region under the effect of climate changes. Hydrology, 4(3), 34.

Rianna, G., Zollo, A.L., Tommasi, P., Paciucci, M., Comegna, L., Mercogliano, P., (2014) Evaluation of the effects of climate changes on landslide activity of Orvieto clayey slope. Procedia Earth Plan. Sci. 9, 54–63.

Riley, K. & Thompson, M. (2017). An uncertainty analysis of wildfire modeling [Chapter 13]. In K. Riley, P. Webley, M. Thompson (eds.).Natural Hazard Uncertainty Assessment: Modeling and Decision Support, Geophysical Monograph 223, First Edition. American Geophysical Union.

Rinaldi, S.M., J.P. Peerenboom, and T.K. Kelly. 2001. Identifying, understanding, and analyzing critical infrastructure interdependencies. IEEE Control Systems Magazine 21(6): 11–25.

RISC-KIT. (2015, November). Coastal Risk Assessment Framework- Guidance Document. Retrieved from Risc-Kit: http://www.risckit.eu/np4/file/383/RISC_KIT_D2.3_CRAF_Guidance.pdf

RISC-KIT. Retrieved 14 December 2019, from http://www.risckit.eu/np4/toolbox/

Risse, L.M., Nearing, M.A., Nicks, A.D., & Laflen, J.M. (1993). Error assessment in the universal soil loss equation. Soil Science Society of America Proceedings, 57(3), 825-33.

Rizzi, J., Torresan, S., Critto, A., Zabeo, A., Brigolin, D., Carniel, S., … Marcomini, A. (2015). Climate change impacts on marine water quality: The case study of the Northern Adriatic sea. Marine Pollution Bulletin. https://doi.org/10.1016/j.marpolbul.2015.06.037

Rizzi, Jonathan, Gallina, V., Torresan, S., Critto, A., Gana, S., & Marcomini, A. (2016). Regional Risk Assessment addressing the impacts of climate change in the coastal area of the Gulf of Gabes (Tunisia). Sustainability Science, 11(3), 455–476. https://doi.org/10.1007/s11625-015-0344-2

Roberts, S., Nielsen, O., Gray, D., & Sexton, J. (2015). ANUGA User Manual. (May), jg. https://doi.org/10.13140/RG.2.2.12401.99686

Robinson, P., Botzen, W.J.W. (2018). The impact of regret and worry on the threshold level of concern for flood insurance demand: Evidence from Dutch homeowners. Judgment and Decision Making, 13(3): 237-245.

Robinson, P., Botzen, W.J.W. (2019a). Flood insurance demand and probability weighting: The influences of regret, worry, locus of control and the threshold of concern heuristic. Water Resources and Economics https://doi.org/10.1016/j.wre.2019.100144

Robinson, P., Botzen, W.J.W. (2019b). Determinants of probability neglect and risk attitudes for disaster risk: An online experimental study of flood insurance demand among homeowners. Risk Analysis, 39(11): 2514-2527.

Roder, G. *et al.* (2017) 'Assessment of Social Vulnerability to Floods in the Floodplain of Northern Italy', Weather, Climate, and Society, 9(4), pp. 717–737. doi: 10.1175/WCAS-D-16-0090.1.

Rogelj J., Popp A., Calvin K., Luderer G., Emmerling J., Gernaat D., Fujimori S., Strefler J., Hasegawa T., Marangoni G., Krey V., Kriegler E., Riahi K., van Vuuren D., Doelman J., Drouet L., Edmonds J., Fricko O., Harmsen M., Havlík P., Humpenöder F., Stehfest E., and M. Tavoni (2018), "Scenarios towards limiting global-mean temperature increase below 1.5°C",Nature Climate Change, Vol. 8(3)

Rojas O., Vrieling A., & Rembold F. (2011): Assessing drought probability for agricultural areas in Africa with coarse resolution remote sensing imagery. Remote Sensing of Environment, 115: 343-352. doi:10.1016/j.rse.2010.09.006

Rokitzki, M. (2017). National Adaptation Plans Thailand - Theory of Multi-Criteria Analysis. Retrieved 12 December 2019, from https://es.slideshare.net/UNDP-Adaptation/national-adaptation-plans-thailand-theory-of-multicriteria-analysis

Roodman, D. (2015). "EXTREME: Stata module to fit models used in univariate extreme value theory," Statistical Software Components S457953, Boston College Department of Economics, revised 18 Dec 2017.

Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., Boote, K. J., Thorburn, P., Antle, J. M., Nelson, G. C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G., Winter, J. M. (2013). The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies. Agricultural and Forest Meteorology, 170, 166–182. https://doi.org/10.1016/j.agrformet.2012.09.011

Rosqvist, T., Molarius, R., Virta, H., & Perrels, A. (2013). Event tree analysis for flood protection - An exploratory study in Finland. Reliability Engineering and System Safety, 112, 1–7. https://doi.org/10.1016/j.ress.2012.11.013

Rosselló-Nadal, J. (2014). How to evaluate the effects of climate change on tourism. Tourism Management, 42, 334–340. https://doi.org/10.1016/J.TOURMAN.2013.11.006

Rothermel, R.C. (1972). A mathematical model for predicting fire spread in wildland fuels. Service Intermountain Forest and Range Experiment Station, INT-115. Ogden, Utah: USDA Forest Service

Rozenberg, J., Espinet Alegre, X., Avner, P., Fox, C., Hallegatte, S., Koks, E., Rentschler, J. and Tariverdi, M., 2019. From A Rocky Road to Smooth Sailing: Building Transport Resilience to Natural Disasters. The World Bank

Ruijters, E., & Stoelinga, M. (2015). Fault tree analysis: A survey of the state-of-the-art in modeling, analysis and tools. Computer Science Review, 15, 29–62. https://doi.org/10.1016/j.cosrev.2015.03.001

Russi, D., & Tabara, J. NAIADE. Retrieved 16 December 2019, from http://www.ivm.vu.nl/en/Images/MCA5_tcm234-161531.pdf

Russo, S., A. Dosio, R. G. Graversen, J.Sillmann, H. Carrao, M. B. Dunbar, A. Singleton, P. Montagna, P. Barbola, and J. V. Vogt, 2014: Magnitude of extreme heat waves in present climate and their projection in a warming world, J. Geophys. Res. Atmos., 119(12),500–512

Ruth Dittrich, Adam Butler, Tom Ball, Anita Wreford and Dominic Moran, Making real options analysis more accessible for climate change adaptation. An application to afforestation as a flood management measure in the Scottish Borders, Journal of Environmental Management, 10.1016/j.jenvman.2019.05.077, 245, (338-347), (2019).

Rydman, M. (2018). Application of the Peaks-Over-Threshold Method on Insurance Data. U.U.D.M. Project Report 2018:32. Upsala University. https://uu.diva-portal.org/smash/get/diva2:1231783/FULLTEXT01.pdf

Salis, M., Ager, A.A., Arca, B., Finney, M.A., Bacciu, V., Duce, P., Spano, D. (2013). Assessing exposure of human and ecological values to wildfire in Sardinia, Italy. International Journal of Wildland Fire, 22, 549-565. https://doi.org/10.1071/WF11060.

Salis, M., Del Giudice, L., Arca, B., Ager, A.A., Alcasena-Urdiroz, F., Lozano, O., Bacciu, V., Spano, D., Duce, P. (2018). Modeling the effects of different fuel treatment mosaics on wildfire spread and behavior in a Mediterranean agro-pastoral area. Journal of Environmental Management, 212, 490-505. https://doi.org/10.1016/j.jenvman.2018.02.020.

Sanches M F, Mwangi E, Ouma G, Opere A 2013 Drought Vulnerability Assessment in Kenya. Deltares. DEWFORA Project report -

San-Miguel-Ayanz, J., Schulte, E., Schmuck, G., Camia, A., Strobl, P., Liberta, G., Giovando, C., Boca, R., Sedano, F., Kempeneers, P., McInerney, D., Withmore, C., Santos De Oliveira, S., Rodrigues, M., Durrant, T., Corti, P., Oehler, F., Vilar, L., Amatulli, G. (2012). Comprehensive monitoring of wildfires in Europe: the European Forest Fire Information System (EFFIS). In J. Tiefenbacher (ed.). Approaches to Managing Disaster - Assessing Hazards, Emergencies and Disaster Impacts (87-108) . Retrieved from https://www.intechopen.com/books/approaches-to-managing-disaster-assessing-hazards-emergencies-and-disaster-impacts/comprehensive-monitoring-of-wildfires-in-europe-the-european-forest-fire-information-system-effis-

Santini, M., Caccamo, G., Laurenti, A., Noce, S., & Valentini, R. (2010). A multi-component GIS framework for desertification risk assessment by an integrated index. Applied Geography, 30 (3), 394-415.

Saxton, K. E., Rawls, W. J. (2006): Soil Water Characteristic Estimates by Texture and Organic Matter for Hydrologic Solutions. Soil Sci. Soc. Am. J. 70, 1569–1578. URL web page (for downloading the hydraulic properties calculator): http://hydrolab.arsusda.gov/soilwater/Index.htm

Sayad, S. (2011). *Real time data mining*. Cambridge: Self-Help Publishers.

Scandizzo, P.L., (2011). Climate Change Adaptation and Real Option Evaluation. CEIS Working Paper No. 232. Available at SSRN: https://ssrn.com/abstract=2046955 or http://dx.doi.org/10.2139/ssrn.2046955

Ščasný, M., Massetti, E., Melichar, J., Carrara, S. (2015). Quantifying the ancillary benefits of the representative concentration pathways on air quality in Europe. Environmental & Resource Economics, 62(2), pp. 383–415. https://doi.org/10.1007/s10640-015-9969-y.

Scawthorn, C., Flores, P., Blais, N., Seligson, H., Tate, E., Chang, S., Mifflin, E., Thomas, W., Murphy, J., Jones, C. and Lawrence, M., 2006. HAZUS-MH flood loss estimation methodology. II. Damage and loss assessment. Natural Hazards Review, 7(2), pp.72-81.

Schär, C., Ban, N., Fischer, E. M., Rajczak, J., Schmidli, J., Frei, C., ... & O'Gorman, P. A. (2016). Percentile indices for assessing changes in heavy precipitation events. Climatic Change, 137(1-2), 201-216.

Schelhaas, M-J., Hengeveld, G., Moriondo, M., Reinds, G.J., Kundzewicz, Z.W., Maat, H., Bindi, M. (2010). Assessing risk and adaptation options to fires and windstorms in European forestry. Mitigation and Adaptation Strategies for Global Change, 15, 681–701. https://doi.org/10.1007/s11027-010-9243-0

Schröter, D., Cramer, W., Leemans, R., Arnell, N.W., Prentice, I.C., Arau, M.B., Bondeau, A., Bugmann, H., Carter, T.R., Gracia, C.A., Vega-leinert, A.C. De, Erhard, M., Klein, R.J.T., Lavorel, S., Kankaanpa, S., Mitchell, T.D., Reginster, I. and Rounsevell, M. 2005. Ecosystem Service Supply and Vulnerability to Global Change in Europe. Science., pp.1333–1337.

Schröter, K., Kreibich, H., Vogel, K., Riggelsen, C., Scherbaum, F. and Merz, B., 2014. How useful are complex flood damage models?. Water Resources Research, 50(4), pp.3378-3395.

Scoccimarro, E., Fogli, P. G., & Gualdi, S. (2017). The role of humidity in determining scenarios of perceived temperature extremes in Europe. Environmental Research Letters, 12(11), 114029.

Scoccimarro, E., Gualdi, S., Bellucci, A., Zampieri, M., & Navarra, A. (2013). Heavy precipitation events in a warmer climate: Results from CMIP5 models. Journal of climate, 26(20), 7902-7911.

Scoccimarro, E., Villarini, G., Vichi, M., Zampieri, M., Fogli, P. G., Bellucci, A., & Gualdi, S. (2015). Projected changes in intense precipitation over Europe at the daily and subdaily time scales. Journal of climate, 28(15), 6193-6203.

Scott, D., Rutty, M., Amelung, B., & Tang, M. (2016). An inter-comparison of the Holiday Climate Index (HCI) and the Tourism Climate Index (TCI) in Europe. Atmosphere, 7(6). https://doi.org/10.3390/atmos7060080

Seynave I., Gegout J.C., Hervé J.C., & Dhôte J.F. (2008). Is the spatial distribution of European beech (Fagus sylvatica L.) limited by its potential height growth? Journal of Biogeography, 35(10), 1851-1862.

Shao, Y., Yang, Y., Wang, J., Song, Z., Leslie, L.M., Dong, C., Zhang, Z., Lin, Z., Kanai, Y., Yabuki, S., & Chun, Y. (2003). Northeast Asian dust storms: Real-time numerical prediction and validation. J. Geophys. Res., 108(D22), 4691.

Sharples, J.J., McRae, R.H.D., Weber, R.O., Gill, A.M. (2009). A simple index for assessing fire danger rating. Environmental Modelling and Software, 24, 764-774. https://doi.org/10.1016/j.envsoft.2008.11.004

Shelton, C. 2014. Climate change adaption in fisheries and aquaculture - compilation of initial examples. Page FAO Fisheries and Aquaculture Circular NO. 1088.

Sherbinin, A. De, Bukvic, A., Rohat, G., Gall, M., Mccusker, B., Virginia, W., Preston, B., Apotsos, A., Fish, C., Kienberger, S., Muhonda, P., Wilhelmi, O., Macharia, D., Shubert, W., Sliuzas, R., Tomaszewski, B. and Zhang, S. 2019. Climate Vulnerability Mapping : A Systematic Review and Future Prospects. Wiley Interdisciplinary Reviews: Climate Change.

Shin, Y. J., and P. Cury. 2001. Exploring fish community dynamics through size-dependent trophic interactions using a spatialized individual-based model. Aquatic Living Resources 14:65–80.

Siad, S. M., Iacobellis, V., Zdruli, P., Gioia, A., Stavi, I., & Hoogenboom, G. (2019). A review of coupled hydrologic and crop growth models. Agricultural Water Management, 224, 105746. https://doi.org/10.1016/j.agwat.2019.105746

Sillmann, J., Kharin, V. V., Zhang, X., Zwiers, F. W., & Bronaugh, D. (2013a). Climate extremes indices in the CMIP5 multimodel ensemble: Part 1. Model evaluation in the present climate. Journal of Geophysical Research: Atmospheres, 118(4), 1716-1733.

Sillmann, J., Kharin, V. V., Zwiers, F. W., Zhang, X., & Bronaugh, D. (2013b). Climate extremes indices in the CMIP5 multimodel ensemble: Part 2. Future climate projections. Journal of geophysical research: atmospheres, 118(6), 2473-2493.

Simelton E, Fraser E, Termansen M, Forster, P, Dougill, A J.(2009) environmental science & policy 12 438–452

Sinclair, S. J., White, M. D., & Newell, G. R. (2010). How useful are species distribution models for managing biodiversity under future climates? Ecology and Society, 15(1). https://doi.org/10.5751/ES-03089-150108

Sirca, C., Salis, M., Arca, B., Duce, P., Spano, D. (2018). Assessing the performance of fire danger indexes in a Mediterranean area. iForest, 11, 563-571. https://doi.org/10.3832/ifor2679-011

Sirca, C., Spano, D., Duce, P., Delogu, G., Cicalò, G.O. (2007). Performance of a newly developed integrated fire rating index in Sardinia, Italy. In X.D. Viegas (ed.). Proceedings of "Wildfire 2007 - 4th International Wildland Fire Conference", Seville (Spain) 13-17 May 2007. Ministry of Environment, Madrid, Spain and Junta de Andalucia, Seville, Spain.

Sivakumar, M. V. K., Motha, R. P., Wilhite, D. A., & Wood, D. A. (2011). AGRICULTURAL DROUGHT INDICES. Proceedings of the WMO/UNISDR Expert Group Meeting on Agricultural Drought Indices, 2-4 June 2010, Murcia, Spain. Agricultural Drought Indices Proceedings of a WMO Expert Meeting held in Murcia, Spain. Geneva.

Sivapalan, M, Konar, M., Srinivasan, V., Chhatre, A., Wutich, A., Scott, C. A., & Wescoat, J. L. (2014). Socio-hydrology: Use-inspired water sustainability science for the Anthropocene. Earth's Future, 2, 225–230. https://doi.org/10.1002/2013EF000164

Sivapalan, Murugesu, Savenije, H. H. G., & Blöschl, G. (2012). Socio-hydrology: A new science of people and water. Hydrological Processes, 26(8), 1270–1276. https://doi.org/10.1002/hyp.8426

Skelhorn, C. P., Levermore, G., & Lindley, S. J. (2016). Impacts on cooling energy consumption due to the UHI and vegetation changes in Manchester, UK. Energy and Buildings, 122, 150–159. https://doi.org/10.1016/j.enbuild.2016.01.035

Skourtos, M., Damigos D, Kontogianni A., Tourkolias C., Markandya, A., Abadie, L. M, Sainz de Murieta, E., Galarraga, I., Wellman, J. and A. Hunt (2016). Future values for adaptation assessment. Deliverable 2.2, Econadapt FP7 research project. Available at https://econadapt.eu/sites/default/files/docs/Deliverable%202-2%20approved%20for%20publishing_0.pdf

Skovsgaard, J.P., & Vanclay J.K. (2008). Forest site productivity: a review of the evolution of dendrometric concepts for even-aged stands. Forestry, 81(1), 12-31.

Slager, K., A. Burzel, E.Bos, K. de Bruijn, D. Wagenaar, H. Winsemius, L. Bouwer, M. van der Doef (2016), User Manual Delft-FIAT version 1, website: publicwiki.deltares.nl/display/DFIAT/Delft-FIAT+Home)

Smit, B., Burton, I., Klein, R. J., and Street, R.: The science of adaptation: a framework for assessment, Mitig. Adapt. Strat. Global Change, 4, 199–213, 1999.

Smith, B., Prentice, C. and Sykes, M.T. 2001. Representation of vegetation dynamics in the modelling of terrestrial ecosystems: comparing two contrasting approaches within Eur-opean climate space. Global Ecology and Biogeography. 10, pp.621–637.

Smith, C. D. (2014). Modelling migration futures: development and testing of the Rainfalls Agent-Based Migration Model – Tanzania. Climate and Development, 0(0): 1–15.

Smith, K.R., A. Woodward, D. Campbell-Lendrum, D.D. Chadee, Y. Honda, Q. Liu, J.M. Olwoch, B. Revich, and R. Sauerborn, 2014: Human health: impacts, adaptation, and co-benefits. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 709-754.

Smith, M. (1992): CROPWAT: A computer program for irrigation planning and management (No. 46). Food & Agriculture Org.

Smith, P., Smith, J.U., Powlson, D.S., McGill, W.B., Arah, J.R.M., Chertov, O.G., Coleman, K., Franko, U., Frolking, S., Jenkinson, D.S., Jensen, L.S., Kelly, R.H., Klein-Gunnewiek, H., Komarov, A., Li, C., Molina, J.A.E., Mueller, T., Parton, W.J., Thornley, J.H.M., & Whitmore, A.P. (1997). A comparison of the performance of nine soil organic matter models using seven long-term experimental datasets. In Evaluation and comparison of soil organic matter models using datasets from seven long-term experiments. Geoderma, 81, 153-225.

SMR Project. (2018). RESILIENCE MATURITY MODEL. https://smr-project.eu/fileadmin/user_upload/Documents/Resources/WP_7/SMR-handbook-www.pdf

SOPAC 2005. Building Resilience in SIDS Collaborators: The Environmental Vulnerability Index.

Soteriades, A.D., Murray-Rust, D., Trabucco, A. & Metzger, M.J. (2017). Understanding global climate change scenarios through bioclimate stratification. Environmental Research Letters, 12, 084002.

Sperotto, A., Molina, J. L., Torresan, S., Critto, A., Pulido-Velazquez, M., & Marcomini, A. (2019). A Bayesian Networks approach for the assessment of climate change impacts on nutrients loading. Environmental Science and Policy, 100(March), 21–36. https://doi.org/10.1016/j.envsci.2019.06.004

Sperotto, Anna, Molina, J.-L., Torresan, S., Critto, A., & Marcomini, A. (2017). Reviewing Bayesian Networks potentials for climate change impacts assessment and management: A multi-risk perspective. Journal of Environmental Management, 202, 320–331.

Spinoni, J. *et al.* (2019) 'A new global database of meteorological drought events from 1951 to 2016', Journal of Hydrology: Regional Studies. Elsevier, 22, p. 100593. doi: 10.1016/J.EJRH.2019.100593.

SREX, Seneviratne, S.I., Nicholls, N., Easterling, D., Goodess, C.M., Kanae, S., Kossin, J., Luo, Y., Marengo, J., McInnes, K., Rahimi, M., Reichstein, M., Sorteberg, A., Vera, C., Zhang, X. (2012). Changes in climate extremes and their impacts on the natural physical environment. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. Cambridge University Press, Cambridge, UK, and New York, NY, USA, pp. 109–230 (A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC)).

Stahl, K., Blauhut, V., Kohn, I., Acácio, V., Assimacopoulos, D., Bifulco, C., ... Urquijo, J. 2012. A European drought impact report inventory (EDII): Design and test for selected recent droughts in Europe. (DROUGHT-R&SPI technical report; No. 3). Wageningen: Wageningen Universiteit.

Stehfest, E., van Vuuren, D., Kram, T., Bouwman, L., Alkemade, R., Bakkenes, M., Biemans, H., Bouwman, A., den Elzen, M., Janse, J., Lucas, P., van Minnen, J., Müller, C., Prins, A. (2014), Integrated Assessment of Global Environmental Change with IMAGE 3.0. Model description and policy applications, The Hague: PBL Netherlands Environmental Assessment Agency.

Steiger, R., Scott, D., Abegg, B., Pons, M., & Aall, C. (2019). A critical review of climate change risk for ski tourism. Current Issues in Tourism, 22(11), 1343–1379. https://doi.org/10.1080/13683500.2017.1410110

Stephenson , A.G and E. Gilleland (2005). Software for the analysis of extreme events: The current state and future directuibs, Extremes 8, 87-109

Stern, N. (2013), “The structure of economic modeling of the potential impacts of climate change: grafting gross underestimation of risk onto already narrow science models”, Journal of Economic Literature, 51 838–859.

Stern, N. (2016), “Economics: Current climate models are grossly misleading”, Nature, 530(7591), 407-409.

Stöckle, C. O., Donatelli, M., & Nelson, R. (2003). CropSyst, a cropping systems simulation model. European Journal of Agronomy, 18(3–4), 289–307. https://doi.org/10.1016/S1161-0301(02)00109-0

Stöckle, C. O., Kemanian, A. R., Nelson, R. L., Adam, J. C., Sommer, R., & Carlson, B. (2014). CropSyst model evolution: From field to regional to global scales and from research to decision support systems. Environmental Modelling & Software, 62, 361–369. https://doi.org/10.1016/j.envsoft.2014.09.006

Stockton, P.H., & Gillette, D.A. (1990). Field measurement of the sheltering effects of vegetation on erodible land surfaces. Land Degrad. Rehabil., 2, 77–85.

Sullivan, A.L. (2009a). Wildland surface fire spread modelling, 1990–2007, 1: Physical and quasi-physical models. International Journal of Wildland Fire, 18, 349–368. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.840.1596&rep=rep1&type=pdf

Sullivan, A.L. (2009b). Wildland surface fire spread modelling, 1990–2007, 2: Empirical and quasi-empirical models. International Journal of Wildland Fire, 18(4), 369–386. https://doi.org/10.1071/WF06142

Sullivan, A.L. (2009c). Wildland surface fire spread modelling, 1990–2007, 3: Simulation and mathematical analogue models. International Journal of Wildland Fire, 18(4), 387–403. https://doi.org/10.1071/WF06144

Sutanto S, van der Weert M, Wanders N, Blauhut V and Van Lanen H (2019) Moving from drought hazard to impact forecasts . Nature Communications 10:4945

Tainio, *et al.* (2014). Conservation of grassland butterflies in Finland under a changing climate. Regional Environmental Change. REC-D-13-00375., 2014. DOI 10.1007/s10113-014-0684-y.

Takeshita, T. (2004) “Detailed Discussion On The Multiplier Effect Of Public Investment In Japan: Simulations Using Short Term Multi-sector Econometric Model”, Journal of Applied Input-Output Analysis, Vol. 10: 39-64

Taylor, K. E. (2001). Summarizing multiple aspects of model performance in a single diagram. Journal of Geophysical Research: Atmospheres, 106(D7), 7183-7192.

Terti, G., Ruin, I., Anquetin, S., & Gourley, J. J. (2015). Dynamic vulnerability factors for impact-based flash flood prediction. Natural Hazards, 79(3), 1481–1497. https://doi.org/10.1007/s11069-015-1910-8

Terzi, S., Torresan, S., Schneiderbauer, S., Critto, A., & Marcomini, A. (2019). A comparative review of multi-risk modelling methodologies for climate change adaptation in mountain regions. Journal of Environmental Management, 3(1). https://doi.org/10.1016/j.jenvman.2018.11.100

Teule, T., Appeldoorn, M., Bosma, P., D.D., S., Koks, E., & De Moel, H. (2020). The vulnerability of solar panels to hail. Climate-KIC.

Thacker, S., S. Kelly, R. Pant, and J.W. Hall. 2017b. Evaluating the Benefits of Adaptation of Critical Infrastructures to Hydrometeorological Risks. Risk Analysis 38(1): 134–150.

Thielen, J., Bartholmes, J., Ramos, M. H., & De Roo, A. (2009). The European flood alert system: Part 1: Concept and development. Hydrology and Earth System Sciences, 13(2), 125–140. https://doi.org/10.5194/hess-13-125-2009

Thistlethwaite, J., Minano, A., Blake, J.A., Henstra, D., Scott, D. (2018). Application of re/insurance models to estimate increases in flood risk due to climate change. Geoenvironmental Disasters, 5(8): 1-13.

Thompson, L. M. (1986). Climatic Change, Weather Variability, and Corn Production. Agronomy Journal, 78(4), 649–653. https://doi.org/10.2134/agronj1986.00021962007800040019x

Thonicke, K., Venevsky, S., Sitch, S., Cramer, W. (2001). The role of fire disturbance for global vegetation dynamics: coupling fire into a Dynamic Global Vegetation Model. Global Ecology and Biogeography, 10, 661–677. https://doi.org/10.1046/j.1466-822X.2001.00175.x

Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., and G.J. de Vries (20155), "An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production", Review of International Economics, 23(3), 575–605
Todd-Brown, K.E.O., Randerson, J.T., Post, W.M., Hoffman, F.M., Tarnocai, C., Schuur, E.A.G., Allison, S.D. (2013). Causes of variation in soil carbon simulations from CMIP5 earth system models and comparison with observations. Biogeosciences, 10(3), 1717–1736.

Tol, R. S. J. (2006), "Multi-Gas Emission Reduction for Climate Change Policy: An Application of FUND", Energy Journal, 27, 235–250.

Tol, R. S. J. (2007). "The Double Trade-Off between Adaptation and Mitigation for Sea Level Rise: An Application of FUND", Mitigation and Adaptation Strategies for Global Change, 12, pp. 741–753.

Toloo G., FitzGerald, G., Aitken, P., Verrall, K. and S. Tong (2013) Evaluating the effectiveness of heat warning systems: systematic review of epidemiological evidence. International Journal of Public Health (2013) 58:667–681.

Torresan, S., Furlan, E., Critto, A., Michetti, M., & Marcomini, A. (2017). Egypt's coastal vulnerability to sea level rise and storm surge, (E., O. (Ed.), 13th International MEDCOAST Congress on Coastal and Marine Sciences, Engineering, Management and Conservation, MEDCOAST 2017. Mediterranean Coastal Foundation), 675–686. https://doi.org/ISBN: 978-605856528-9

Torresan, S., Zabeo, A., Rizzi, J., Critto, A., Pizzol, L., Giove, S., & Marcomini, A. (2010). Risk assessment and decision support tools for the integrated evaluation of climate change impacts on coastal zones. 2010 International Congress on Environmental Modelling and Software Modelling for Environment's Sake, Fifth Biennial Meeting, (2007), 8.

Trenberth, K. E., *et al.* (2007). Observations: Surface and atmospheric climate change, in Climate Change 2007: The Physical Science Basis, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, edited by S. Solomon *et al.*, pp. 235– 336, Cambridge Univ. Press, New York.

Turner, B. L., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Hovelsrud-Broda, G., Kasperson, J., Kasperson G., Luers, A., Martello, M., Mathiesen, S., Naylor, R., Polsky, C., Pulsipher, A., Schiller, A., Selin, H., and Tyler, N.: Illustrating the coupled human–environment system for vulnerability analysis: three case studies, Proc. Natl. Acad. Sci., 100, 8080–8085, 2005. And

UNDRR. (2019). Global Assessment Report on Disaster Risk Reduction. Geneva, Switzerland. Retrieved from https://gar.undrr.org/sites/default/files/reports/2019-05/full_gar_report.pdf

UNESCO. (2018). Climate Risk Informed Decision Analysis (CRIDA) - Collaborative Water Resources Planning for an Uncertain Future. https://agwaguide.org/docs/CRIDA_Sept_2019.pdf

UNFCCC, nd. MULTICRITERIA ANALYSIS (MCA). Retrieved 11 December 2019, from https://www4.unfccc.int/sites/nwpstaging/Pages/item.aspx?ListItemId=22946&ListUrl=/sites/nwp/Lists/MainDB

United Nation Convention to Combat Desertification (1994). United Nations Convention to Combat Desertification. UN General Assembly.

University of Notre Dame (2018) ND - GAIN: Notre Dame Global Adaptation Initiative, Notre Dame Global Adaptation Initiative. Available at: https://gain.nd.edu/our-work/country-index/methodology/ (Accessed: 30 November 2018).

Unterberger, C., Hudson, P., Botzen, W.J.W., Schroeer, K., Steininger, K. (2019). Future public sector flood risk and risk sharing arrangements: An assessment for Austria. Ecological Economics, 156: 153-163.

Uran, O., & Janssen, R. (2003). Why are spatial decision support systems not used? Some experiences from the Netherlands. Computers, Environment and Urban Systems, 27(5), 511–526.

US Army Corps of Engineers. (2010). HEC-RAS River Analysis System. In User's Manual - Version 4.1 - CPD-68. https://doi.org/CPD-68

US Army Corps of Engineers. (2015). HEC-HMS Hydrologic Modeling System. In User's Manual - Version 4.1 - CPD-74A. Davis, CA.

Valentine, H.T., Mäkelä, A. (2005). Bridging process based and empirical approaches to modeling tree growth. Tree Physiology, 25(7), 769-779.

Van Der Heijden, K. 1996. Scenarios - the art of strategic conversation. Wiley.

Van Der Knijff, J. M., & De Roo, A. (2008). LISFLOOD - Distributed Water Balance and Flood Simulation Model - Revised User Manual.

Van Der Knijff, J.M., Younis, J. and De Roo, A.P.J., 2010. LISFLOOD: a GIS-based distributed model for river basin scale water balance and flood simulation. International Journal of Geographical Information Science, 24(2), pp.189-212.

Van der Krogt, W. (2010): Technical report: RIBASIM 7.01. Deltares, Delft.

van der Pol, T.D., van Ierland, E.C. and Weikard, H.-P. (2013) Optimal Dike Investments under Uncertainty and Learning about Increasing Water Levels. Journal of Flood Risk Management 7(4). DOI: 10.1111/jfr3.12063. https://doi.org/10.1111/jfr3.12063

van Diepen, C. A., Wolf, J., Keulen, H., & Rappoldt, C. (1989). WOFOST: a simulation model of crop production. Soil Use and Management, 5(1), 16–24. https://doi.org/10.1111/j.1475-2743.1989.tb00755.x

van Ginkel, K., Koks, E., Alfierei, L., Dottori, F., & Feyen, L. (2019). River flood disruptions of the European road network: a tipping point for Europe? DMDU 2019 Annual Meeting.

Van Ierland, E. C., De Bruin, K., Dellink, R. B., & Ruijs, A. (2007). A qualitative assessment of climate adaptation options and some estimates of adaptation costs.

Van Loon A, Stahl, k, Di Baldassarre, G.,Clark, J., Rangecroft, S., Wanders, N., Gleeson, T., Van Dijk, A I.J.M., Tallaksen, L M., Hannaford, J., Uijlenhoet, R., Teuling, A J., Hannah, D M., Sheffield, J., Svoboda, M., Verbeiren, B., Wagener, T., Van Lanen, H A.J. Drought in a human-modified world: Reframing drought definitions, understanding, and analysis approaches. Hydrolgy and Earth system Sciences. Vol 20(9) 3631-3650

Van Os, J.J.A.M., S. Caires and M.R.A. van Gent, 2011: Guidelines for metocean data analysis, ISOPE 2011, Maui.

van Wagner, C.E. (1987). Development and structure of the Canadian forest fire weather index. Forestry technical report 35. Ottawa, Canada: Canadian Forestry Service

Varela-Ortega, C., Blanco-Gutiérrez, I., Esteve, P., Bharwani, S., Fronzek, S. and Downing, T.E. 2016. How can irrigated agriculture adapt to climate change? Insights from the Guadiana Basin in Spain. Regional Environmental Change. 16(1), pp.59–70.

Vautard, R., Gobiet, A., Jacob, D., Belda, M., Colette, A., Déqué, M., ... & Halenka, T. (2013). The simulation of European heat waves from an ensemble of regional climate models within the EURO-CORDEX project. Climate Dynamics, 41(9-10), 2555-2575

Vautard, R., Gobiet, A., Sobolowski, S., Kjellström, E., Stegehuis, A., Watkiss, P., Mendlik, T., Landgren, O., Nikulin, G., Teichmann, C., Jacob, D., 2014. The European climate under a 2 °C global warming. Envrion Res Let 9, 034006.

Venables, W. N., and C. M. Dichmont. 2004. GLMs, GAMs and GLMMs: an overview of theory for applications in fisheries research. Fisheries Research 70:319–337.

Venturas, M. D., E. D. MacKinnon, H. L. Dario, A. L. Jacobsen, R. B. Pratt, and S. D. Davis, 2016: Chaparral shrub hydraulic traits, size, and life history types relate to species mortality during California's historic drought of 2014. PLoS One, 11, e0159145, https://doi .org/10.1371/journal.pone.0159145.

Verdin, J., Klaver, R. (2002): Grid-cell-based crop water accounting for the famine early warning system. Hydrological Processes, 16(8): 1617-1630.

Vergeynst, Lidewei, Bogaerts, J., Baert, A., Kips, L., & Steppe, K. (2013). New type of vulnerability curve gives insight in the hydraulic capacitance and conductivity of the xylem. In Kathy Steppe (Ed.), Acta Horticulturae (Vol. 991, pp. 341–347). Presented at the 9th International workshop on Sap Flow, Leuven, Belgium: International Society for Horticultural Science (ISHS).

Vernimmen, R., Hooijer, A., & Pronk, M. (2020). New ICESat-2 Satellite LiDAR Data Allow First Global Lowland DTM Suitable for Accurate Coastal Flood Risk Assessment. *Remote Sensing*, *12*(17), 2827.

Viavattene, C., Priest, S., Owen, D., Parker, D., Micou, P., & Ly, S. (2016). INDRA model: for a better assessment. Planning, Foresight and Risk Analysis Proceedings of the ISCRAM 2016 Conference (p. 9). Rio de Janeiro: Tapia, Antunes, Bañuls, Moore and Porto de Albuquerque, eds.

Vogt, J., de Jager,A., Magni, D., Mazzeschi, M., Carrão, H., Barbosa, P., 2016. Improvements in the Global Drought Observatory (GDO). JRC contribution to the Emergency Response Coordination Centre (ERCC). Technical Report JRC, Ispra, Italy\Vogt, J.V., Naumann, G., Masante, D., Spinoni, J., Cammalleri, C., Erian, W., Pischke, F., Pulwarty, R., Barbosa, P., Drought Risk Assessment. A conceptual Framework. EUR 29464 EN, Publications Office of the European Union, Luxembourg, 2018. ISBN 978-92-79-97469-4, doi:10.2760/057223, JRC113937

Vousdoukas, Michail (2015): European Extreme Storm Surge level - Historical. European Commission, Joint Research Centre (JRC) [Dataset] PID: http://data.europa.eu/89h/0026aa70-cc6d-4f6f-8c2f-554a2f9b17f2

Vousdoukas, M. I. *et al.* (2018) 'Global probabilistic projections of extreme sea levels show intensification of coastal flood hazard', Nature Communications. Nature Publishing Group, 9(1), p. 2360. doi: 10.1038/s41467-018-04692-w.

Vousdoukas, Michail; Mentaschi, Lorenzo; Voukouvalas, Evangelos; Verlaan, Martin; Feyen, Luc (2016): Extreme Sea level - RCP45. European Commission, Joint Research Centre (JRC) [Dataset] PID: http://data.europa.eu/89h/e9e42344-119d-479e-9bc7-57400d12a8a2

Wamsler, C. 2017. Stakeholder involvement in strategic adaptation planning: Transdisciplinarity and co-production at stake? Environmental Science & Policy. 75, pp.148–157.

Ward, P.J., Jongman, B., Aerts, J.C., Bates, P.D., Botzen, W.J., Loaiza, A.D., Hallegatte, S., Kind, J.M., Kwadijk, J., Scussolini, P. and Winsemius, H.C., 2017. A global framework for future costs and benefits of river-flood protection in urban areas. Nature climate change, 7(9), p.642.

Wardekker, A. (2018). Resilience Principles as a Tool for Exploring Options for Urban Resilience. Solutions, 9.

Wasserman, S. and Faust, K. 1994. Social network analysis : methods and applications. Cambridge, UK: Cambridge University Press.

Watkiss, P. and Hunt, A. (2012). Projection of economic impacts of climate change in sectors of Europe based on bottom up analysis: human health. Climatic Change, 2012, Volume 112, Number 1, Pages 101-126. DOI: 10.1007/s10584-011-0342-z.

Watkiss, P. and Hunt, A. (2012). Cost-effectiveness analysis: Decision Support Methods for Adaptation, MEDIATION Project, Briefing Note 2. Funded by the EC's 7FWP
Watkiss, P . and Hunt, A, Blyth, W (2013). Real Options Analysis: Decision Support Methods for Adaptation, MEDIATION Project, Briefing Note 4. Funded by the EC's 7FWP. Available at https://www.weadapt.org/sites/weadapt.org/files/legacy-new/knowledge-base/files/1202/5204fe5fd75f9real-options-analysis.pdf

Watkiss, P., Hunt, A., Blyth, W. and Dyszynski, J (2014). The use of new economic decision support tools for adaptation assessment: A review of methods and applications, towards guidance on applicability. Climatic Change. 132: 401. https://doi.org/10.1007/s10584-014-1250-9

Watson, J.E.M., Iwamura, T. and Butt, N. 2013. Mapping vulnerability and conservation adaptation strategies under climate change. Nature Climate Change. 3(11), pp.989–994.

Weißhuhn, P., Müller, F. and Wiggering, H. 2018. Ecosystem Vulnerability Review : Proposal of an Interdisciplinary Ecosystem Assessment Approach. Environmental Management. 61, pp.904–915.

Whalley, J. and Wigle, R. (1991). "The International Incidence of Carbon Taxes". In R. Dornbush and J. M. Poterba (Eds.), Economic Policy Responses to Global Warming. Cambridge: MIT Press.

WHO (2007). Global tuberculosis control: surveillance, planning, financing. WHO report. Geneva, World Health Organization (WHO/HTM/TB/2007.376).

WHO Europe (2017). Protecting health in Europe from climate change: 2017 Update. WHO Regional Office for Europe. Published by WHO Europe.

Wilhelmi, O. V. and Wilhite, D. A.: Assessing vulnerability to agricultural drought: a Nebraska case study, Nat. Hazards, 25, 37–58, 2002

Wilhite, D. A. and M. H. Glantz. 1985. "Understanding the Drought Phenomenon: The Role of Definitions." Drought Mitigation Center Faculty Publications. 20. http://digitalcommons.unl.edu/ droughtfacpub/20. WMO

Williams, J. R., Jones, C. A., Kiniry, J. R., & Spanel, D. A. (1989). The EPIC Crop Growth Model. Transactions of the ASAE, 32(2), 0497–0511. https://doi.org/10.13031/2013.31032

Willis, I., Gibin, M., Barros, J., & Webber, R. (2014). Applying neighbourhood classification systems to natural hazards: a case study of Mt Vesuvius. Natural Hazards, 70(1), 1–22. https://doi.org/10.1007/s11069-010-9648-9

Wischmeier, W.H., & Smith, D.D. (1978). Predicting rainfall erosion losses: a guide to conservation planning. USDA agriculture handbook. Washington DC: USDA.

Witt, A., Eilts, M. D., Stumpf, G. J., Jonhson, J., Dewayne Mitchell, E., & Thomas, K. W. (1998). An Enhanced Hail Detection Algorithm for the WSR-88D. Weather and Forecasting, 286-303.

WMO and GWP (World Meteorological Organization and Global Water Partnership). 2014. National Drought Management Policy Guidelines: A Template for Action (D.A.

Wilhite). Integrated Drought Management Programme (IDMP) Tools and Guidelines Series 1. WMO and GWP: Geneva and Stockholm.
(WMO), W. M., Klein, A. M., Zwiers, F. W., & Zhang, X. (2009). Guidelines of analysis of extremes in a changing climate in support of informed decisions for adaptation. Geneva: WNO. Retrieved January 27, 2020, from https://library.wmo.int/index.php?lvl=notice_display&id=138#.Xle6waj0mUk

WMO, UNCCD and FAO, 2013: High Level Meeting on National Drought Policy, Geneva, 11–15 March 2013. Policy Document: National Drought Management Policy. Geneva,

Woodward, Michelle; Kapelan, Zoran; Gouldby, Ben (2014): Adaptive Flood Risk Management Under Climate Change Uncertainty Using Real Options and Optimization.Risk Analysis, Vol. 34, No. 1. DOI: 10.1111/risa.12088

World Bank, 2019. Assessing Drought Hazard and Risk: Principles and Implementation Guidance. Washington, DC: World Bank www.droughtcatalogue.com

Worldfishcenter. (n.d.). worldfishcenter. https://www.worldfishcenter.org/why-fish.

Wouters, L., Boon, M., van Putten, D., van t' Veen, B., Koks, E., & de Moel, H. (2020). A hail climatology of the Netherlands. Amsterdam: Climate-KIC.

Xiong, W., Asseng, S., Hoogenboom, G., Hernandez-Ochoa, I., Robertson, R., Sonder, K., … Gerard, B. (2020). Different uncertainty distribution between high and low latitudes in modelling warming impacts on wheat. Nature Food, 1(1), 63–69. https://doi.org/10.1038/s43016-019-0004-2

Xoplaki, E., González-Rouco, J. F., Luterbacher, J., & Wanner, H. (2003). Mediterranean summer air temperature variability and its connection to the large-scale atmospheric circulation and SSTs. Climate dynamics, 20(7-8), 723-739.

Xu, C. (2002). Hydrologic Models. In C. Xu (Ed.), Hydrologic Models (2002nd ed., Vol. 72). Uppsala, Sweden: Uppsala University. Department of Earth Sciences Hydrology.

Xu, L., Cui, S., Tang, J., Nguyen, M., Liu, J., & Zhao, Y. (2019). Assessing the adaptive capacity of urban form to climate stress: A case study on an urban heat island. Environmental Research Letters, 14(4). https://doi.org/10.1088/1748-9326/aafe27

Yusta, J.M., G.J. Correa, and R. Lacal-Arántegui. 2011. Methodologies and applications for critical infrastructure protection: State-of-the-art. Energy Policy 39(10): 6100–6119.

Yuzhi Cai, Dominic Hames. Minimum sample size determination for generalized extreme value distribution. Communications in Statistics - Simulation and Computation, Taylor & Francis, 2010, 40 (01), pp.87-98. ff10.1080/03610918.2010.530368ff. ffhal-00651154f

Zaidi, R. Z. (2018). Beyond the Sendai indicators: Application of a cascading risk lens for the improvement of loss data indicators for slow-onset hazards and small-scale disasters. International Journal of Disaster Risk Reduction, 30(March), 306–314. https://doi.org/10.1016/j.ijdrr.2018.03.022

Zampieri, M., Russo, S., di Sabatino, S., Michetti, M., Scoccimarro, E., & Gualdi, S. (2016). Global assessment of heat wave magnitudes from 1901 to 2010 and

implications for the river discharge of the Alps. Science of the Total Environment, 571, 1330-1339.
Zarafshani K, Sharafi Lm, Azadi H and Van Passel S (2016) Vulnerability assessment models to drought: toward a conceptual framework. Sustainabiliyt vol 8 pp 588

Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. Environmental Reviews, 19, 333– 349. https://doi.org/10.1139/a11-013

Zhang, W., Villarini, G., Scoccimarro, E., & Vecchi, G. A. (2017). Stronger influences of increased CO2 on subdaily precipitation extremes than at the daily scale. Geophysical Research Letters, 44(14), 7464-7471.

Zhang, X., Alexander, L., Hegerl, G. C., Jones, P., Tank, A. K., Peterson, T. C., ... & Zwiers, F. W. (2011). Indices for monitoring changes in extremes based on daily temperature and precipitation data. Wiley Interdisciplinary Reviews: Climate Change, 2(6), 851-870

Zhang, Z., & Moore, J. C. (2014). Mathematical and physical fundamentals of climate change. Elsevier.

Zhou, Y., Li, N., Wu, W., Wu, J., & Shi, P. (2014). Local Spatial and Temporal Factors Influencing Population and Societal Vulnerability to Natural Disasters. Risk Analysis, 34(4), 614–639. https://doi.org/10.1111/risa.12193

Zio, E. 2009. Reliability engineering: Old problems and new challenges. Reliability Engineering & System Safety 94(2): 125–141.

Zscheischler, J., & Seneviratne, S. I. (2017). Dependence of drivers affects risks associated with compound events. Science Advances, 3(6), 1–11. https://doi.org/10.1126/sciadv.1700263

Zscheischler, J., Westra, S., Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., … Wahl, T. (2018). Future climate risk from compound events. Nature Climate Change, 1.

Zwiers, F. W., Alexander, L. V., Hegerl, G. C., Knutson, T. R., Naveau, P., Nicholls, N., ... & Wang, X. L. (2011). Challenges in estimating and understanding recent changes in the frequency and intensity of extreme climate and weather events. Community paper on climate extremes. In Proceedings of World Climate Research Programme Open Science Conference, Denver, CO, WCRP.

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