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The Role of Risk Components and Spatial Dependence in Flood Risk Estimations

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Location and Date

Ayşe Duha Metin Usta

Summary

Flooding is a vast problem in many parts of the world, including Europe. It occurs mainly due to extreme weather conditions (e.g. heavy rainfall and snowmelt) and the consequences of flood events can be devastating. Flood risk is mainly defined as a combination of the probability of an event and its potential adverse impacts. Therefore, it covers three major dynamic components: hazard (physical characteristics of a flood event), exposure (people and their physical environment that being exposed to flood), and vulnerability (the elements at risk). Floods are natural phenomena and cannot be fully prevented. However, their risk can be managed and mitigated. For a sound flood risk management and mitigation, a proper risk assessment is needed. First of all, this is attained by a clear understanding of the flood risk dynamics. For instance, human activity may contribute to an increase in flood risk. Anthropogenic climate change causes higher intensity of rainfall and sea level rise and therefore an increase in scale and frequency of the flood events. On the other hand, inappropriate management of risk and structural protection measures may not be very effective for risk reduction. Additionally, due to the growth of number of assets and people within the flood-prone areas, risk increases. To address these issues, the first objective of this thesis is to perform a sensitivity analysis to understand the impacts of changes in each flood risk component on overall risk and further their mutual interactions. A multitude of changes along the risk chain are simulated by regional flood model (RFM) where all processes from atmosphere through catchment and river system to damage mechanisms are taken into consideration. The impacts of changes in risk components are explored by plausible change scenarios for the mesoscale Mulde catchment (sub-basin of the Elbe) in Germany.

A proper risk assessment is ensured by the reasonable representation of the real-world flood event. Traditionally, flood risk is assessed by assuming homogeneous return periods of flood peaks throughout the considered catchment. However, in reality, flood events are spatially heterogeneous and therefore traditional assumption misestimates flood risk especially for large regions. In this thesis, two different studies investigate the importance of spatial dependence in large scale flood risk assessment for different spatial scales. In the first one, the "real" spatial dependence of return period of flood damages is represented by continuous risk modelling approach where spatially coherent patterns of hydrological and meteorological controls (i.e. soil moisture and weather patterns) are included. Further the risk estimations under this modelled dependence assumption are compared with two other assumptions on the spatial dependence of return periods of flood damages: complete dependence (homogeneous return periods) and independence (randomly generated heterogeneous return periods) for the Elbe catchment in Germany. The second study represents the "real" spatial dependence by multivariate dependence models. Similar to the first study, the three different assumptions on the spatial dependence of return periods of flood damages are compared, but at national (United Kingdom and Germany) and continental (Europe) scales. Furthermore, the impacts of the different models, tail dependence, and the structural flood protection level on the flood risk under different spatial dependence assumptions are investigated.

The outcomes of the sensitivity analysis framework suggest that flood risk can vary dramatically as a result of possible change scenarios. The risk components that have not

received much attention (e.g. changes in dike systems and in vulnerability) may mask the influence of climate change that is often investigated component.

The results of the spatial dependence research in this thesis further show that the damage under the false assumption of complete dependence is 100 % larger than the damage under the modelled dependence assumption, for the events with return periods greater than approximately 200 years in the Elbe catchment. The complete dependence assumption overestimates the 200-year flood damage, a benchmark indicator for the insurance industry, by 139 %, 188 % and 246 % for the UK, Germany and Europe, respectively. The misestimation of risk under different assumptions can vary from upstream to downstream of the catchment. Besides, tail dependence in the model and flood protection level in the catchments can affect the risk estimation and the differences between different spatial dependence assumptions.

In conclusion, the broader consideration of the risk components, which possibly affect the flood risk in a comprehensive way, and the consideration of the spatial dependence of flood return periods are strongly recommended for a better understanding of flood risk and consequently for a sound flood risk management and mitigation.

Zusammenfassung

Hochwasser sind ein großes Problem und treten hauptsächlich aufgrund extremer Wetterbedingungen (z. B. starker Regen und Schneeschmelze) auf. Die Folgen von Hochwasserereignissen können verheerend sein. Das Konzept des Hochwasserrisikos beinhaltet die drei Komponenten: Gefahr, Exposition und Vulnerabilität. Hochwasser sind natürliche Phänomene und können nicht sicher verhindert werden. Das Risiko kann jedoch gesteuert und gemindert werden. Für ein solides Hochwasserrisikomanagement und die Minderung des Risikos ist eine ordnungsgemäße Risikobewertung und ein klares Verständnis der Hochwasserrisikodynamik erforderlich. Beispielsweise verursacht der anthropogene Klimawandel eine höhere Intensität der Niederschläge und einen Anstieg des Meeresspiegels und damit eine Zunahme des Ausmaßes und der Häufigkeit von Hochwasserereignissen. Andererseits können unangemessene strukturelle Schutzmaßnahmen, das Anwachsen von Vermögenswerten und eine steigende Anzahl betroffener Personen in den hochwassergefährdeten Gebieten das Risiko erhöhen. Um diese Probleme zu adressieren, besteht ein Ziel dieser Arbeit aus der Durchführung einer Sensitivitätsanalyse, um die Auswirkungen von Änderungen in jeder Hochwasserrisikokomponente auf das Gesamtrisiko und deren Wechselwirkungen untereinander zu verstehen.

Eine angemessene Risikobewertung wird auch durch die korrekte k Darstellung des realen Hochwasserereignisses erreicht. Traditionell wird das Hochwasserrisiko bewertet, indem homogene Wiederkehrintervalle von Hochwasserspitzen im gesamten Einzugsgebiet angenommen werden. In der Realität sind Hochwasserereignisse jedoch räumlich heterogen, weshalb die traditionelle Annahme von Homogenität das Hochwasserrisiko insbesondere für große Einzugsgebiete falsch einschätzt. In dieser Arbeit wird die Bedeutung der räumlichen Abhängigkeit bei der Bewertung des Hochwasserrisikos in großem Maßstab in zwei Studien für verschiedene räumliche Skalen untersucht. In der ersten Untersuchung wird die „reale" räumliche Abhängigkeit durch einen kontinuierlichen Risikomodellierungsansatz dargestellt. Zusätzlich werden die Risikoabschätzungen unter dieser modellierten Abhängigkeitsannahme mit zwei weiteren Annahmen zur räumlichen Abhängigkeit der Wiederkehrintervalle von Hochwasser verglichen: vollständige Abhängigkeit und Unabhängigkeit für das Elbeeinzugsgebiet in Deutschland. Die zweite Studie repräsentiert die „reale" räumliche Abhängigkeit durch ein copula-basiertes Abhängigkeitsmodell. In ähnlicher Weise werden die drei verschiedenen Annahmen zur räumlichen Abhängigkeit der Wiederkehrintervalle von Hochwasser auf nationaler und kontinentaler Ebene verglichen. Außerdem wird der Einfluss von „Tail-dependences" im Modell sowie von Hochwasserschutzmaßnahmen auf die räumliche Abhängigkeit untersucht.

Die Ergebnisse dieser Arbeit unter Anwendung des Sensitivitätsanalyse-Frameworks zeigen, dass das Hochwasserrisiko aufgrund möglicher Änderungsszenarien dramatisch variieren kann. Der Einfluss des Klimawandels kann durch Änderungen anderer Risikokomponenten (z. B. Änderungen der Deichsysteme und der Vulnerabilität) überdeckt werden. Die Untersuchung zur räumlichen Abhängigkeit zeigen, dass der Schaden unter der Annahme vollständiger Abhängigkeit für Ereignisse mit Wiederkehrintervalle von mehr als ungefähr 200 Jahren im Elbeeinzugsgebiet 100 % größer als der Schaden unter modellierter Abhängigkeit. Die Annahme vollständiger

Abhängigkeit überschätzt den 200-jährigen Hochwasserschaden, einen Referenzindikator für die Versicherungsbranche, um 139 %, 188 % und 246 % für Vereinigte Königreich, Deutschland und Europa. Die Fehleinschätzung des Hochwasserrisikos kann unter verschiedenen Annahmen von Abhängigkeit zwischen Oberlauf und Unterlauf eines Einzugsgebietes stark variieren. Zudem können „Tail-dependences" im Modell sowie der Hochwasserschutz im Einzugsgebiet die Ergebnisse der Risikoabschätzung, unter verschiedenen Annahmen der räumlichen Abhängigkeit, beeinflussen.

Abschließend wird eine umfangreiche Berücksichtigung der Risikokomponenten und insbesondere der räumlichen Abhängigkeit von Wiederkehrintervallen stark empfohlen, um das Hochwasserrisiko und damit dessen Management und Minderung besser verstehen zu können.

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Contents

Abbreviations

1-D	One-dimensional space
2-D	Two-dimensional space
A	Atmosphere
a.s.l.	above sea level
AD	Anderson-Darling test
AMS	Annual Maximum Streamflow
AoI	Areas of Influence
ATKIS	Authorative Topographic-Cartographic Information System, (in German)
BKG	Federal Agency for Cartography and Geodesy in Germany, (in German)
BMVBW	Federal Ministry of Transport and Digital Infrastructure, (in German)
BPI	Construction price indices, (in German)
BÜK	Overview soil map, (in German)
C	Catchment
CCM	Constant of channel maintenance
CORINE	COoRdinated INformation on the Environment
CPU	Central Processing Unit
CRED	Centre for Research on the Epidemiology of Disasters
CUDA	Compute Unified Device Architecture
CvM	Cramer-von Mises test
d	day
DEM	Digital Elevation Model
DESTATIS	German Federal Statistical Office, (in German)
df	degree of freedom
DFRA	Derived Flood Risk Analysis
DLM	Digital Basic Landscape Model
DLR	German Aerospace Center, (in German)
E	Exposure
EA	Asset Values

EAD	Expected Annual Damage
EAP	Expected Annual Population exposed
EC	European Commission
EEA	European Environment Agency
EFAS	European Flood Awareness System
EL	Land Use
EU	European Union
EUR	Euro (European Monetary Unit)
FLEMOps	The Flood Loss Estimation Model for the private sector
GDP	Gross Domestic Product
GDP	Gross Domestic Product
GEV	Generalized Extreme Value
GPU	Graphics Processing Unit
GRDC	Global Runoff Data Centre
H	Hazard
HQ_{100}	100-year discharge
ICPR	International Commission for the Protection of the River Rhine
IKSE	International Commission for the Protection of the Elbe, (in German)
IPCC	Intergovernmental Panel on Climate Change
ISI	Institute for Scientific Information
JRC	Joint Research Centre
mNSE	modified Nash-Sutcliffe efficiency
nearPD	Nearest Positive Definite matrix
NSE	Nash-Sutcliffe Efficiency
R	River System
RFM	Regional Flood Model
RIM	Regional Inundation Model
RWG	Regional Weather Generator
SCE-UA	Shuffled Complex Evolution method developed at The University of Arizona
SWIM	Soil and Water Integrated Model
UK	United Kingdom

UN-DESA	The United Nations Department of Economic and Social Affairs
UNISDR	The United Nations Office for Disaster Risk Reduction
USA	United States of America
USD	United States Dollar
V	Vulnerability

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Chapter 1 – Introduction

Natural hazards result in serious and extensive consequences. In Europe, flooding is one of the major natural hazards which causes far-reaching damages and disruptions. Over the period 1998-2018, around €60 billion of total economic damage and around 520 fatalities were recorded in Europe due to catastrophic flood events (Munich Re, 2019). The costliest flood events occurred in 2002 and 2013 in the central Europe. In August 2002, the total economic damage was estimated around €15 billion where Germany was the hardest hit, experiencing a damage of €9 billion (Munich RE, 2004). During the 2002 event, approximately 600,000 people were affected with around 80 fatalities in 11 countries (EEA, 2003). In June 2013, flooding caused a total economic damage of €12 billion, majority of which belonged to Germany, and 25 people lost their lives (Munich RE, 2013).

Owing to the destructive consequences of floods, the areas exposed and vulnerable to flood risk should be carefully identified and managed. It is commonly stated that flood risk depends on three dynamic components: hazard, exposure and vulnerability (Kron, 2005; Cardona et al., 2012; UNISDR, 2013). Hazard refers to magnitude and frequency of natural or anthropogenic flood events that possibly have negative impacts on exposed and vulnerable elements. Although, hazard has been perceived the same meaning as risk by time, at present it is well recognized that it is a component of risk. Exposure refers to people and assets which possibly experience the flood event. Vulnerability refers to susceptibility of people and assets at risk and the coping capacity to handle adverse impacts of flood event. Often, the usage of exposure and vulnerability is mistakenly combined. In fact, they are different. For instance, being exposed but not vulnerable to flood event is possible, however being vulnerable definitely requires being exposed to flood event.

It is obvious that flood risk changes over time due to its dynamic components. It is likely to see a considerable change in flood risk in the next few decades. At present, climate change is more pronounced than even before, and flood hazard is expected to occur more frequently in the future (IPCC, 2019). On the other hand, according to UN-DESA (2019), urban population grew more than 4-fold and it will continue to increase. Therefore, an effective flood risk assessment and then a sound flood risk management gain high importance.

Flood risk management is defined as comprehensive and continuous societal analysis, assessment and mitigation of flood risk (Schanze et al., 2006). In the past, traditional risk management mainly aimed to reduce risk by river training and construction of structural defences. However, this often overlooked that structural measures can alter public risk perception (e.g. Su et al., 2017). For instance, people feel safe and they settle along the river valley. This decreases flood awareness and precaution. Over past two or three decades, with the necessity of a holistic way of risk management, a shift has been observed by also including non-structural measures (e.g. flood warning systems, land use regulations, flood emergency preparedness plans, flood-proofing of buildings, and insurance) in the risk management. This integration in risk management can be seen in the European Floods Directive (EC, 2007) which provides a legal framework for risk management for all waters across European Union. For example, the reason for reduced damage in 2013 event is indicated by the improvement in flood risk management on many levels after 2002 event (Thieken et al., 2016). These improvements were especially observed in (i) spatial planning and urban development, (ii) individual level mitigation and preparedness measures, (iii) flood warnings and coordination of disaster response and (iv) maintenance of flood defences.

1.1. Changes in flood risk

During last few decades, economic damages due to floods have considerably increased (e.g. EEA, 2019). This increase is often attributed to increasing number of people and assets, also called socio-economic trends leading to an increase in flood exposure (e.g. Barredo, 2009; IPCC, 2012).

In fact, human activity can have adverse impact also on hazard component, in addition to increase in flood exposure. For instance, urbanization and deforestation decreases infiltration into the soil; improper waste disposal blocks the drainage systems. These can increase and accelerate surface runoff during a flood event (e.g. Kundzewicz and Schellnhuber, 2004; Kundzewicz, 2012). Besides, due to some river training measures (e.g. construction of flood protection measures), which may accelerate the propagation of a flood along the river network, the natural floodplain for peak discharges (flood retention areas) may reduce (e.g. Skublics et al., 2016) and for a certain discharge, higher water levels can be observed.

In addition, anthropogenic climate change may affect the hazard component. This may increase heavy precipitation events as a result of warmer atmosphere. Although there is no clear evidence that climate change influences the increase in flood damages (e.g. Barredo, 2009; Bouwer, 2011), climate change may still affect flood risk. Increase in heavy precipitation may also have a role on increasing damage (e.g. Jongman et al., 2012; EEA, 2019). Flood risk is affected by various drivers at the same time, and hence it is hard to conceive their individual impacts on flood risk. For example, the effect of climate change can be masked by improved early warning systems, strengthened protection measures or better private precaution (e.g. Di Baldassarre et al., 2015; Jongman et al., 2015).

Previous studies used various approaches to understand changes in flood risk. For example, Kreibich et al. (2017) used the approach of paired flood events where consecutive flood events in the same region were compared. They presented that lower damage by the second event is mainly due to significant reductions in vulnerability (e.g. improved risk awareness, preparedness, and organizational emergency management). In another approach, loss normalization studies have been conducted by correcting loss time series for growth in population and wealth, and inflation (e.g. Barredo, 2009; Bouwer, 2011; Visser et al., 2014). These studies suggested that socio-economic development can be the principal driver of the increasing flood damage in Europe. Besides, other data-based approaches focused on the understanding of the impact of single risk drivers. Kreibich et al. (2005) and Bubeck et al. (2012) investigated the role of the implementation of private precaution measures on flood risk by surveying households. Both studies revealed that the implementation of private precaution measures reduced the damage significantly. All of these data-based approaches are useful to better understand change in flood risk; however, they cannot provide detailed information on the impact of each risk driver and their relative contributions to total risk. Therefore, for more detailed analysis, simulation-based approaches are preferred. With the simulation-based approaches contributions of different drivers and past or future changes in flood risk can be estimated by scenario runs. Further, the outcomes highly depend on the case study and scenarios selected. Most of the simulation-based studies focus on changes in hazard (e.g. climate change) and exposure (e.g. changes in land use and assets). They often address climate change as the dominant driver (e.g. Arnell and Gosling, 2016; Bouwer et al., 2010; Feyen et al., 2012; Hattermann et al., 2014; Te Linde et al., 2011). However, in some cases, change in land use and GDP (gross domestic product) can mask the impact of climate change (e.g. Elmer et al., 2012; Muis et al., 2015; Winsemius et al., 2015). In addition, the combination of climate change and socio-economic development scenarios can be more dominant and may lead to significant increases in risk (e.g. Alfieri et al., 2015b; Budiyono et al., 2016; Hall et al., 2003; Lung et al., 2013; Rojas et al., 2013). However, for a more comprehensive analysis with simulation-based approach, change in vulnerability should also be included (UNISDR, 2015; Kreibich et al., 2017).

1.2. Spatial dependence in risk assessments

In order to manage and mitigate flood risk, there should be a comprehensive analysis and an assessment of risk (Meyer et al., 2009). The common concept for a risk assessment often starts with a flood hazard assessment which mainly includes discharge-frequency analysis and/or rainfall-runoff modelling, and hydraulic modelling. The discharge-frequency analysis and rainfall-runoff modelling are used to estimate maximum flood discharges for different return periods. Following this, hydraulic modelling is used to determine flood hazard and risk at the given spatial scale by simulating the flood depths and the extent of flooded area. The complexity of hydraulic models can vary depending on the scale of the analysis from simple interpolation methods to sophisticated and spatially detailed models (Apel et al., 2009). Further, for the risk assessment, hazard information is combined with information on exposure (land-use and asset values) and vulnerability. In this step, different damage models can be used to estimate flood damage (Olesen et al., 2017). The simplest damage assessment considers average unit cost for the inundated area. For a more complex damage assessment, damage model is applied where depth-damage curves are often taken into consideration. The most complex assessment approach calculates damage on an object level. As a final step, by combining the information on flood damage and its corresponding event probability, risk (exceedance probability) curve is constructed. The area under this curve is often estimated to express risk as the expected annual damage (EAD).

The results of flood risk assessment are often in the forms of flood hazard maps and flood risk maps. These communicate flood risk to different target audience such as water management authorities, municipalities or civil protection agencies and broader public (Spachinger et al., 2008). Flood hazard maps include the information on flood characteristics such as flood water depth and inundation extent for certain return periods. Flood risk maps additionally include the information on the consequences of a flood event (e.g. economic damage, number of people affected). However, while producing these maps, the biggest challenge is to satisfy spatial consistency during a flood event, especially for large scale assessment. The traditional approach assumes a number of spatially homogeneous scenarios for certain return periods (e.g. Rhine Atlas (ICPR, 2015)). That is to say, during a flood event with T-year return period, all flooded areas experience T-year flood. Typically, these local T-year flood estimates, based on extreme value statistics at particular gauges, are pieced together to construct flood maps.

Many studies at the global scale (e.g. Ward et al., 2013; Winsemius et al., 2015), at the European scale (e.g. Rojas et al., 2013; Bubeck et al., 2019) and at the national scale (e.g. Hall et al., 2005; Dumas et al., 2013) are based on this traditional assumption of homogeneity. However, in the real world, flood events are spatially heterogeneous due to strongly varying flood generation processes in atmosphere, catchment and river network (e.g. Nied et al., 2017; Vorogushyn et al., 2018). The traditional approach tends to overestimate discharge probabilities at individual gauges over large areas (Thieken et al., 2015).

In the context of flood risk assessment, spatial dependence of flood return periods can be considered using the following approaches. The first one is an event-based simulation approach where stochastic rainfall events are generated as an input to the hydrological model (e.g. Rodda, 2001; Jankowfsky et al., 2016). However, in this approach the return periods of discharge and rainfall are assumed to be equal which is not plausible all the time. The second approach is the application of multivariate distribution functions to estimate the spatial dependence of flood peak discharges at multiple areas (e.g. Keef et al., 2009; Quinn et al., 2019). In this approach, synthetic hydrographs, only based on flood peaks, are produced to estimate inundated areas. These hydrographs may be spatially inconsistent which can be a disadvantage. The third approach is the piece-wise combination of inundation maps and risk estimation for heterogeneous return periods where previously derived homogeneous return period maps are interpolated (Alfieri et al., 2015a, 2016a, 2017). Although, this approach represents spatial dependence, due to the piece-wise combination of inundation maps may result in inconsistencies. The last approach is a long-term continuous simulation of hydrological and hydrodynamic processes considering synthetic time-series of meteorological variables (e.g. Falter et al., 2015). This approach may require high computational costs, but it allows to model spatially consistent flood events. Another advantage of this approach is that flood risk is directly derived from the damage time series instead of time series of peak discharges, hence the difficulties while translating peak discharge probabilities to damage probabilities are resolved.

1.3. Objectives and outline

In a changing world, an effective flood risk management and mitigation can be achieved by performing comprehensive flood risk assessment. This requires detailed research on flood risk dynamics. In this regard, this thesis aims to expand the understanding of changing flood risk and risk assessment through investigating the role of risk components and comparing risk under different spatial dependence assumptions. The role of risk components on overall flood risk is investigated for the Mulde catchment in Germany. The different spatial dependence assumptions are compared for the Elbe catchment in Germany and for Europe.

The above-mentioned objectives of this thesis are addressed in three main chapters. This thesis includes an introductory chapter, three main chapters and a concluding chapter.

Figure 1.1 shows the structure of this thesis, including specific purposes and considered spatial scales in three main chapters. Chapters 2, 3 and 4 are in the form of manuscripts where all of them have been published in peer-reviewed journals.

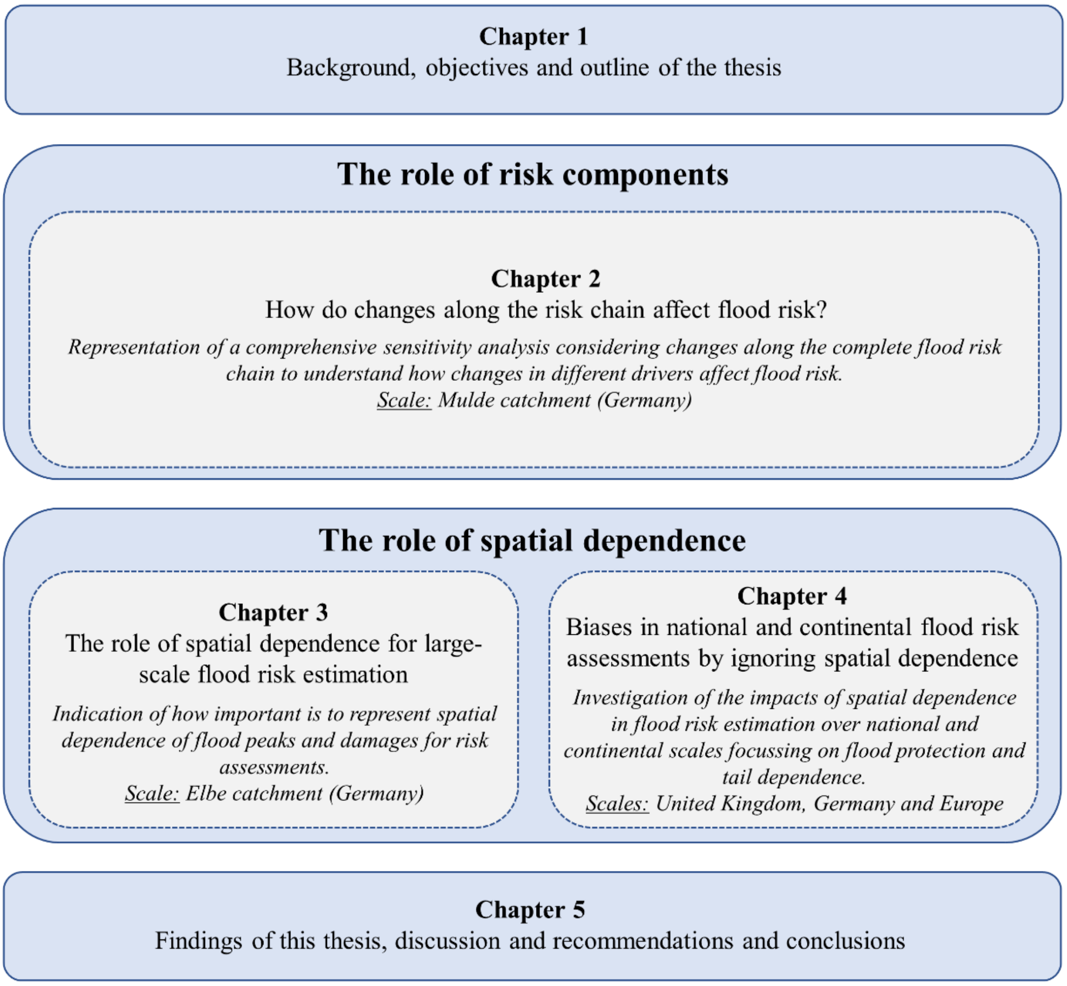

Figure 1.1: Structure of the thesis

While the reason of changing flood hazard in the past and the possibility of changes in the future are widely investigated, studies on changes in flood risk are limited to certain risk components such as climate change or land use change. In the light of flood risk definition, change in flood risk ought to be investigated comprehensively considering whole spectrum of risk components. Therefore, first, the contribution of risk components to the change in flood risk is described in Chapter 2. This aims to help improved flood risk assessment and decision-making process. The following research questions are addressed in Chapter 2.

- How and to what extent do the changes in risk components propagate through risk chain and affect flood risk?
- How is the overall flood risk affected by the changes in risk components for different locations and seasons?

The many studies assess flood risk by assuming spatially homogeneous return periods of flood peaks. However, this assumption is not an appropriate representation of the real-world case. Therefore, the second and third studies investigate the effect of spatial dependence on flood risk estimates at different spatial scales. This is crucial for a thorough flood risk assessment. Chapter 3 considers spatial dependence by continuous modelling of the entire risk chain. Estimated flood risk under this modelled dependence assumption (spatially dependent heterogenous return periods) is compared with flood risk estimates under two different assumptions (limit cases): complete dependence (homogeneous return periods) and complete independence (randomly generated heterogeneous return periods). In this study, the effect of spatial dependence is investigated for the Elbe catchment. Chapter 4 represents spatial dependence by using copula-based dependence models. Similar to the second study, risk estimates under three different assumptions are compared. Contrary to the second study, the effect of spatial dependence is investigated on European scale where results on national scale (for the UK and Germany) are also provided. Because continuous modelling is difficult at the European scale, this study provides insights into the risk estimates with different copula-based dependence models of loss at multiple locations. In addition, the impact of the structural flood protection level is investigated in Chapter 4. The following are addressed in Chapters 3 and 4:

- ❖ What is the bias in risk estimates under the “false” assumptions of spatial dependence of return periods of damages?
- ❖ What is the role of spatial scale, tail dependence in the multivariate dependence model and structural flood protection level on flood risk under the different assumptions of spatial dependence?

1.4. Author contributions

The main chapters of this thesis are produced with a collaboration between the author of this thesis and the co-authors who are represented with their initials. Manuscripts and their author contributions are as follows:

Chapter 2: How do changes along the risk chain affect flood risk?

Authors: Ayse Duha Metin (ADM), Nguyen Viet Dung (NVD), Kai Schröter (KS), Björn Guse (BG), Heiko Apel (HA), Heidi Kreibich (HK), Sergiy Vorogushyn (SV), and Bruno Merz (BM)

ADM, BM, NVD, and SV developed the concept. BM conceived and supervised the study. ADM, NVD, and KS performed simulations. ADM analysed the results. ADM prepared the paper with contributions from all the co-authors. All authors made a substantial contribution to the interpretation of results and provided important ideas to further improve the study.

Chapter 3: The role of spatial dependence for large-scale flood risk estimation

Authors: ADM, NVD, KS, SV, BG, HK, and BM

ADM, BM, NVD, and SV developed the concept. BM conceived and supervised the study. ADM, NVD, and KS performed simulations. ADM analysed the results. ADM prepared the paper with contributions from all the co-authors. All authors made a substantial contribution to the interpretation of results and provided important ideas to further improve the study.

Chapter 4: Biases in national and continental flood risk assessments by ignoring spatial dependence

Authors: NVD, ADM, Lorenzo Alfieri (LA), SV and BM

NVD, BM, SV and ADM developed the concept. BM conceived and supervised the study. NVD, ADM and LA performed simulations. ADM analysed the results. ADM prepared the paper with contributions from all the co-authors.

Chapter 2

How do changes along the risk chain affect flood risk?

Authors: Ayşe Duha Metin, Nguyen Viet Dung, Kai Schröter, Björn Guse, Heiko Apel, Heidi Kreibich, Sergiy Vorogushyn, Bruno Merz

Abstract

Flood risk is impacted by a range of physical and socio-economic processes. Hence, the quantification of flood risk ideally considers the complete flood risk chain, from atmospheric processes through catchment and river system processes to damage mechanisms in the affected areas. Although it is generally accepted that a multitude of changes along the risk chain can occur and impact flood risk, there is a lack of knowledge how and to what extent changes in influencing factors propagate through the chain and finally affect flood risk. To fill this gap, we present a comprehensive sensitivity analysis which considers changes in all risk components, i.e. changes in climate, catchment, river system, land use, assets and vulnerability. The application of this framework to the mesoscale Mulde catchment in Germany shows that flood risk can vary dramatically as consequence of plausible change scenarios. It further reveals that components that have not received much attention, such as changes in dike systems or in vulnerability, may outweigh changes in often investigated components, such as climate. Although the specific results are conditional on the case study area and the selected assumptions, they emphasise the need for a broader consideration of potential drivers of change in a comprehensive way. Hence, our approach contributes to a better understanding of how the different risk components influence the overall flood risk.

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2.1. Introduction

Globally, floods affect more people than any other natural hazard, and the global average annual flood loss has been estimated to amount to more than USD 100 billion (UNISDR, 2015). Flood risk is defined as the likelihood of losses and depends on three factors: hazard, exposure and vulnerability (IPCC, 2012; UNISDR, 2013). Hazard is related to the physical processes with the potential to cause harm ranging from atmospheric via catchment processes to river routing, whereas exposure refers to the elements at risk of flooding. Vulnerability is defined as the susceptibility of the elements at risk to be adversely affected. Typically, exposure is quantified as the number of people and the assets in flood-prone areas, and vulnerability is represented as the damage ratio, i.e. the degree to which elements-at-risk are damaged given hazard impacts. Consequently, flood risk assessments ideally need to consider the entire flood risk chain from the atmospheric processes, through the catchment and river system processes to the damage mechanisms in the affected areas.

It is now well acknowledged that flood risk can change substantially in time, since all three risk factors are dynamic (e.g. Kreibich et al., 2017). The causes of these changes are manifold; they range from human-induced climate change and natural climate variability on decadal or centennial time scales to changes in vulnerability that may act on much shorter time scales (Merz et al., 2010a). The spatial and temporal interdependencies among hazard, exposure and vulnerability and interactions within these risk chain compartments should be considered in flood risk assessment (Merz et al., 2014a; Vorogushyn et al., 2017).

In their study of paired flood events, Kreibich et al. (2017) looked into consecutive flood events that occurred in the same region and attempted to understand what drove the changes in the observed impact. Their collection of case studies revealed the essential role of vulnerability reduction in losses, for instance, via improved risk awareness, preparedness and organizational emergency management. Conversely, they emphasized that different risk drivers act simultaneously; for instance, structural measures can be complemented by non-structural measures.

Another approach to understand changes in flood risk is loss normalization using observed damage data (e.g. Visser et al., 2014). Time series of flood damages usually show increasing trends. To separate the effect of socio-economic development, the original loss time series are corrected for growth in population and wealth, and for inflation. For example, Barredo (2009) normalized losses of large river floods aggregated at the scale of 31 European countries between 1970 and 2006. Since the normalization removed the increasing trend in the original loss values, this study suggested that socio-economic development was the dominant driver of increasing flood damage in Europe. Similar conclusions have been drawn from other loss normalization studies for weather-related hazards (IPCC, 2012; Neumayer and Barthel, 2011; Bouwer, 2011; Visser et al., 2014).

Other data-based studies attempted to understand the influence of single drivers. For instance, Bubeck et al. (2012) surveyed 752 households along the Rhine and found that the implementation of private mitigation measures developed gradually over time with severe floods leading to a stepwise increase in mitigation. They concluded that an improved preparedness triggered by a severe flood in 1993 led to substantial damage reduction during a second flood with similar hazard characteristics in 1995. A survey of 1200 households affected by the Elbe flood in 2002 in Germany suggested that private precautionary measures reduced the damage to the buildings and their contents on the order of 50 % for the most effective measures, i.e. flood-adapted use and adapted interior fitting (Kreibich et al., 2005).

Although data-based approaches have helped to better understand flood risk changes, it is hard to conceive how the causes of flood risk changes and their relative contributions could be deciphered from empirical data only. A major problem is the superposition of several drivers of risk changes. It is easily conceivable that adaptation measures, such as improved early warning systems, strengthened flood protection, or better private precaution, have masked the effect of climate change (Handmer et al., 2012; Di Baldassarre et al., 2015; Jongman et al., 2015; Mechler and Bouwer, 2015). Hence, conclusions from normalization studies, such as there is no evidence for the effect of human-induced climate change on the loss trend (e.g. Barredo, 2009), need to be taken with care. Another limitation of data-based approaches results from the lack of reliable loss data. Loss data are often not available, or are available only for standard economic sectors in developed countries, and large uncertainties reside in reported or reconstructed loss records (Handmer et al., 2012; Merz et al., 2010a; Wirtz et al., 2014).

Simulation-based approaches offer the advantage that the contributions of different drivers can be estimated via scenario runs. Table 2.1 compiles simulation-based studies that investigated past or future changes in river flood risk. The various studies that addressed changes in flood hazard only, for instance as a consequence of climate and land use change, are not included. This selection of studies results from a comprehensive literature search using the following search terms (both in combination and separately) in the ISI Web of Knowledge database: *flood risk, change, damage, climate* and *socioeconomic scenarios* in October 2017. The identified articles were checked for forward and backward citations. We would like to point out that studies focussing on the uncertainties in estimation of hazard, exposure, vulnerability, and their effect on risk estimates were not in the focus of this review.

Table 2.1 shows that all studies addressed climate change. Other changes in flood hazard have not been investigated with the exception of land subsidence by Budiyono et al. (2016). Almost all studies look at changes in exposure, most often in terms of land use change. Changes in asset values are also addressed frequently. In terms of risk indicators, the majority of studies are limited to EAD (expected annual damage).

There is no unanimous conclusion across these simulation-based studies. The results highly depend on the case study and the drivers and scenarios selected. Yet, 5 out of 13 studies conclude that climate change was the dominant driver leading to an increase in flood risk. The other studies indicate different drivers and combinations as more dominant. (For a detailed assessment of these studies see the Supplementary for Chapter 2.)

Although there is a wealth of studies on how and why flood hazard has changed in the past and might change in the future (IPCC, 2012), studies on changes in flood risk are scarce. Data-based approaches are strongly limited due to data availability and methodological problems. Simulation-based studies on changes in flood risk have been limited to climate and land use change and have primarily focussed on future scenarios rather than understanding past changes. Other drivers of risk, such as flood protection measures, have been neglected. This gap is particularly severe in terms of the effects of changes in vulnerability (Merz et al., 2014a; Mechler and Bouwer, 2015). Our systematic literature search did not result in a single simulation-based study which included changes in vulnerability. We can conclude that knowledge about the underlying processes and their contribution to changes in flood risk is still scarce (UNISDR, 2015; Kreibich et al., 2017), and there is a lack of comprehensive studies that take into account the whole spectrum of drivers.

Our study is a contribution to fill this research gap. It analyses how different drivers, including all three components of risk, affect flood risk. Changes in flood risk are evaluated for the catchment scale and two typical up- and downstream sub-basins and for summer and winter seasons. We quantify the sensitivity of flood risk to changes along the flood risk chain, considering all components of the chain. This includes changes in the atmosphere, catchment, river system and affected floodplain areas. Specifically, we consider climate change, implementation of reservoirs in the catchment, flood protection along the rivers, land use change, change in asset values and changes in the vulnerability of flood-affected objects. For each of the six factors, two scenarios with increasing and decreasing change with symmetric deviation from a baseline scenario are derived. Hence, the sensitivity analysis consists of 729 (3^6) scenarios.

This sensitivity analysis is combined with the derived flood risk analysis (DFRA) proposed by Falter et al. (2015). DFRA consists of an end-to-end flood risk assessment based on continuous simulation. A model chain representing the catchment, river network and damage processes is driven by a multi-site stochastic weather generator. DFRA is an extension of the derived flood frequency analysis based on continuous simulation, which has found increasing attention recently (e.g. Haberlandt and Radtke, 2014). A major advantage of DFRA is that all processes, from the flood-triggering precipitation to the damage, are simulated in a spatially consistent way, respecting the spatial dependence of the different processes. Another advantage is the derivation of flood risk directly from the damage time series, generated by the model chain, instead of the discharge time series.

The sensitivity analysis is performed for the Mulde catchment in Germany, which was severely hit by flooding in 2002 and 2013. We use the model chain implemented and calibrated by Falter et al. (2015) for the Mulde catchment. A total of 4000 years of spatial weather fields at daily resolution are generated and used to force the model chain, resulting in daily and spatially explicit fields of streamflow, inundation and damage throughout the catchment. From these datasets, the risk curve (or loss-probability curve) and EAD are calculated. Introducing the change scenarios for the six factors leads to 729 damage time series of 4000 years, which again are used to calculate the flood risk.

The paper is structured in six sections. Section 2.2 describes the study area. Section 2.3 introduces the simulation model chain and the approach used in the sensitivity analysis including the change scenarios. Section 2.4 presents the results of the sensitivity analysis including sub-basin and sub-annual variations. Sections 2.5 and 2.6 provide discussions and conclusions.

Table 2.1: Simulation-based studies on the causes of flood risk changes and their relative contributions. H, E indicate whether changes in hazard or exposure are investigated. (EAD: Expected Annual Damage; EAP: Expected Annual Population exposed).

		Drivers considered								
		Climate change (H)	*Land subsidence (H)*	*Change in GDP (E)*	*Change in population (E)*	*Change in asset values (E)*	*Change in land use (E)*	*Change in cropland area (E)*		
Alfieri et al. (2015)	1990-2080, Europe (28 countries)	✓		✓	✓				EAD, EAP	▪ Combinations of change in climate, in GDP and in population
Arnell and Gosling (2016)	2050, global (20 regions)	✓		✓	✓	✓		✓	EAD, EAP	▪ Climate change
Bouwer et al. (2010)	2040, south Netherlands	✓				✓	✓		EAD, Loss probability curves	▪ Climate change
Budiyono et al. (2016)	2030, Jakarta	✓	✓				✓		EAD	▪ Land subsidence and land use change
Elmer et al. (2012)	1990-2020, Mulde River, Germany	✓				✓	✓		EAD	▪ Land use change
Feyen et al. (2009)	2071-2100, Europe	✓					✓		EAD	▪ Land use change
Feyen et al. (2012)	2071-2100, Europe	✓							EAD, EAP	▪ Climate change
Hall et al. (2003)	2030-2100, England and Wales	✓		✓	✓	✓	✓		EAD, EAP	▪ Change in GDP, asset values, land use and population (socio-economic drivers)
Hattermann et al. (2014)	2011-2100, Germany	✓							EAD	▪ Climate change
Lung et al. (2013)	2011-2040 and 2041-2070, Europe	✓				✓	✓		3 indicators related to 100-year flood: percentage of flooded area; mean water depth of flooded area; percentage of commercial & industrial areas within flooded area (only for 2011-2040)	▪ Combinations of change in climate, in asset value and in land use
Muis et al. (2015)	2000-2030, Indonesia	✓					✓		EAD	▪ Land use change
Rojas et al. (2013)	2000-2080, European Union	✓		✓	✓	✓			EAD, EAP	▪ Change in GDP, asset values and population (socio-economic drivers)
Te Linde et al. (2011)	2030, Rhine catchment	✓					✓		EAD	▪ Climate change

2.2. Study area

Our study area, the Mulde catchment (7115 km²), is a sub-basin of the Elbe River in Germany, which is one of the largest rivers in central Europe. The Mulde River drains the northern part of the Ore Mountains. The Mulde and its major tributaries have a length of around 380 km. The catchment elevation varies between 52 m and 1213 m a.s.l. (above sea level). Approximately 10 % of the catchment area is covered by urban structures. Anhalt-Bitterfeld, located downstream in the Mulde catchment, and Zwickau, located upstream, have been selected as two districts for more detailed analyses (Fig. 2.1). The annual precipitation ranges from 500 to 1100 mm. Although the majority of floods in the Mulde catchment occur in winter, extreme floods tend to occur in summer due to widespread and intensive precipitation. Reservoirs in the Mulde catchment (14 of them have a storage capacity greater than 1 million m^3) are generally used for drinking water supply, but they also have the storage capacity for flood protection (Schädler et al., 2012).

The most extreme floods during the last decades in Germany were observed in August 2002 and June 2013 (Schröter et al., 2015). While the 2002 flood has been the most expensive disaster for Germany to date, the 2013 event has been the most severe flood in hydrological terms in the last 6 decades. Both floods also had severe impacts in the Mulde catchment. A total of 115 and 24 dike failures were observed in the Mulde catchment in 2002 and 2013, respectively (Thieken et al., 2016). Historical documents, going back to the ninth century, show that the Mulde catchment has been hit by large floods associated with high damages before (Petrow et al., 2007). The repeated occurrence of extreme flooding associated with high damages is the primary reason for selecting it as the study area.

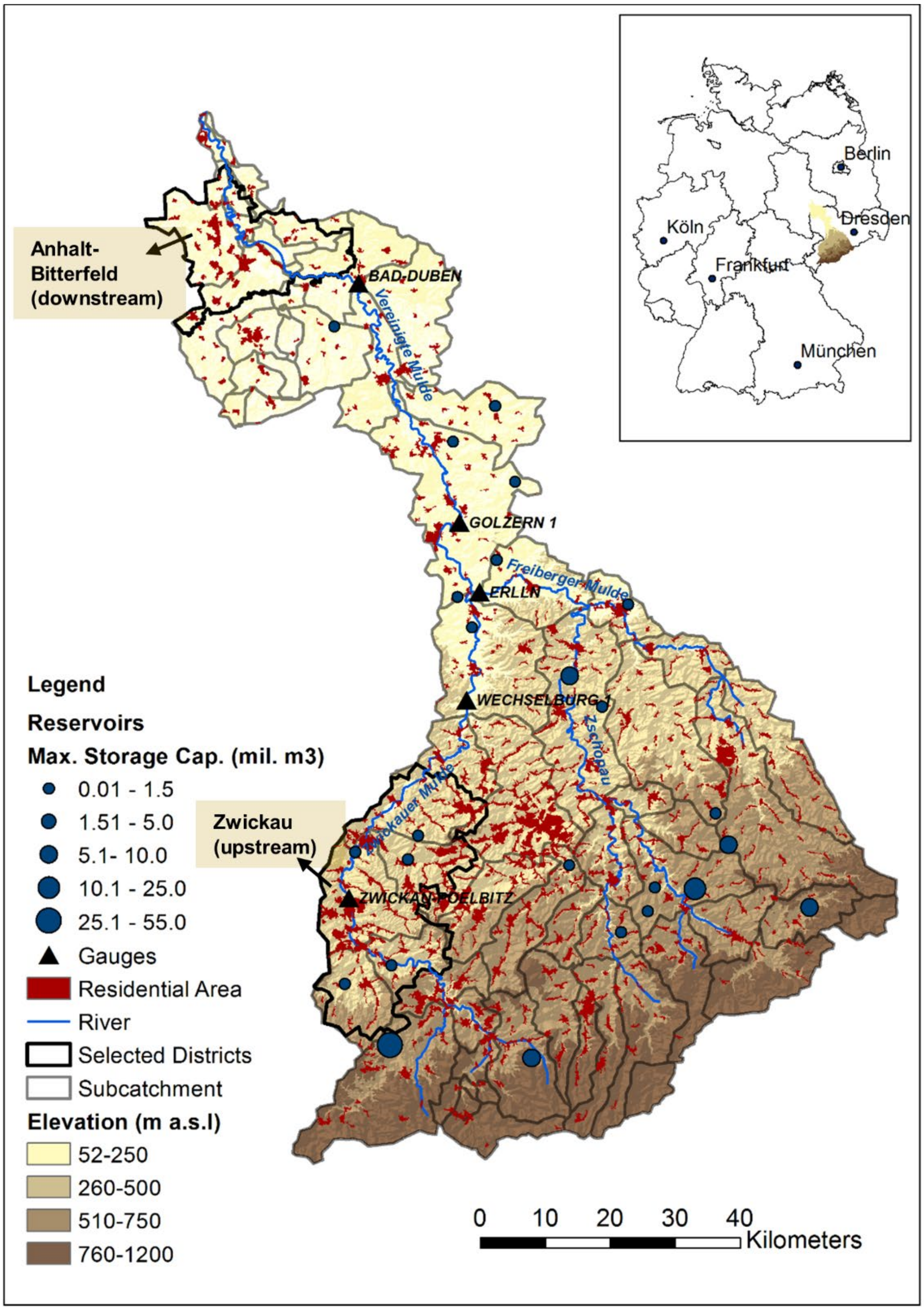

Figure 2.1: Study area of the Mulde catchment, including the main tributaries, reservoirs, and river gauges. The inset shows the location of the catchment within Germany.

2.3. Methods

2.3.1. Flood risk simulation model chain

To simulate the complete flood risk chain, the Regional Flood Model (RFM) is used. RFM consists of a weather generator, rainfall-runoff model, 1-D channel routing model, 2-D hinterland inundation model, and flood loss estimation model for residential buildings. The results of one model are used as input for the next model. Figure 2.2 shows the model chain and gives the most important information on the input data and the characteristics of the different modules. Details about the model chain are given in Falter et al. (2015). The computational demand of the different modules is as follows: 8% Regional Weather Generator (RWG) (coverage: Germany+), 10% Soil and Water Integrated Model (SWIM), 80% Regional Inundation Model (RIM), 2% FLEMOps. Please note that RIM runs on a mixed infrastructure CPU + GPU. The other components run on CPU only.

The model set-up follows the concept of derived flood risk analysis based on continuous simulation proposed by Falter et al. (2015). A weather generator provides spatially consistent meteorological fields which propagate through the entire model chain. In our study, the chain is run on a daily time step for 40 realizations of 100 years resulting in a total time series of 4000 years. Risk estimates are then derived directly from the time series of damage generated by the model chain.

A derived flood risk analysis based on continuous simulation has a number of advantages compared to event-based flood risk estimates. For instance, due to the continuous simulation the antecedent catchment conditions are implicitly considered in the flood generation, and the approach provides the complete flood hydrograph on a daily base. Since all models within the chain are spatially explicit, the approach provides spatially consistent flood events including the river-floodplain and damage processes. Hence, spatial consistency of losses across the catchment is also taken into account. A further advantage is that risk is estimated using the space-time fields of damage. Hence, this approach follows the definition of risk, in which risk is understood as the probability of exceeding a given damage. In contrast, traditional flood risk analyses use the probability of discharge as a proxy for the probability of damage. For a comprehensive discussion see Falter et al. (2015).

Note that our model set-up is the same as in Falter et al. (2015). The only difference is that we consider reservoirs in the rainfall-runoff module. The different modules along the risk model chain are described in the following.

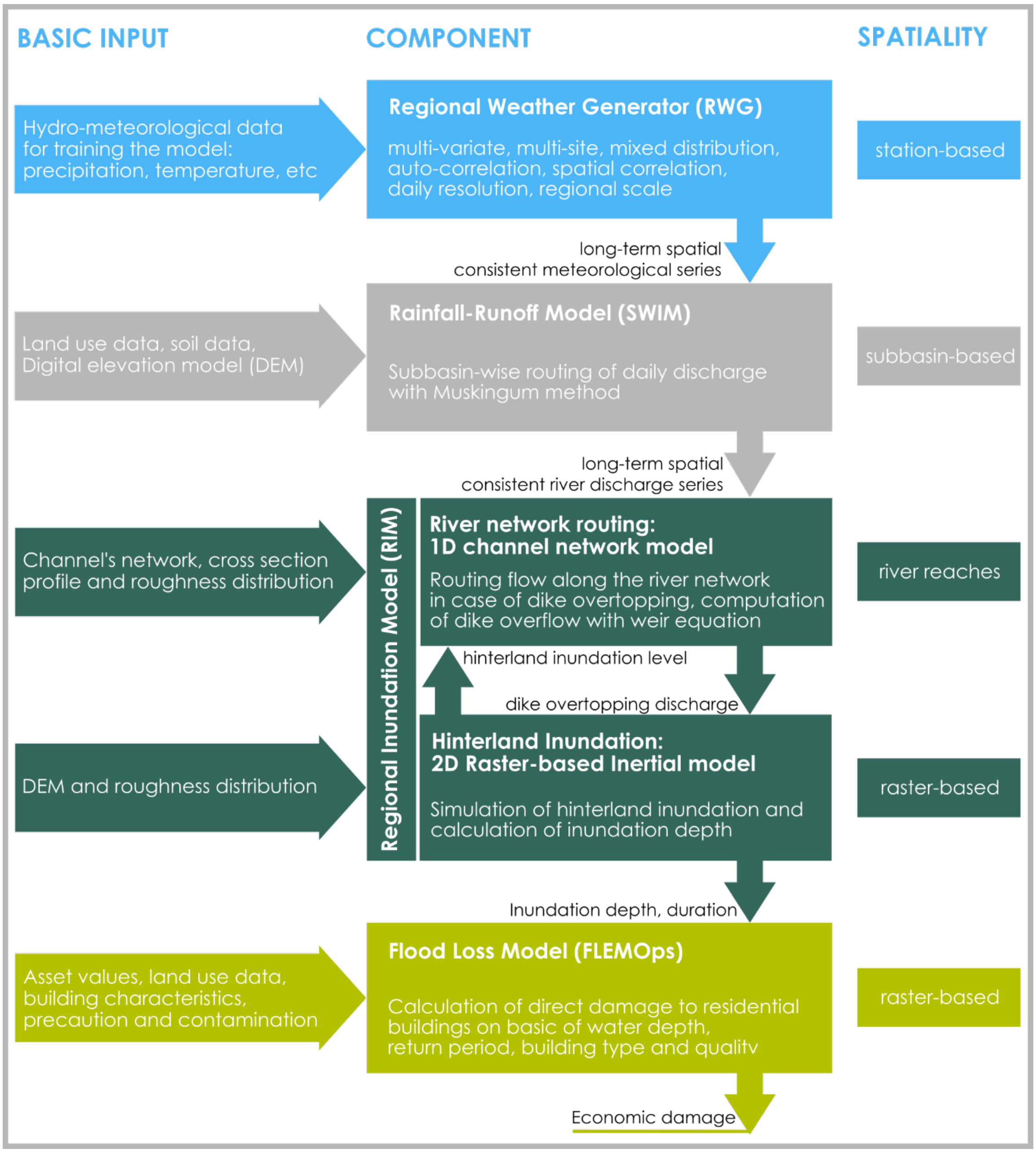

Figure 2.2: Flood risk model chain: regional flood model (RFM).

2.3.1.1. Regional weather generator RWG

The meteorological input is obtained from the multi-site, multi-variate weather generator RWG (Regional Weather Generator) proposed by Hundecha et al. (2009) and further developed by Hundecha and Merz (2012). This model is designed to generate synthetic weather at the regional scale, i.e. several tens of thousands to hundreds of thousands of square kilometres. It creates daily time series of climatic variables at multiple sites in two steps: generation of daily precipitation series through a multivariate autoregressive model (which uses a mixed gamma and generalized Pareto distribution) and generation of daily maximum, minimum, and mean temperature and solar radiation using Gaussian distribution. Both temperature and solar radiation depend on the state of precipitation.

The weather generator is set up for the whole of Germany, including the upstream areas of the Elbe, Danube and Rhine catchments outside of Germany. It is used to generate long synthetic meteorological data considering daily climate observations for the period from 1951 to 2003 at 528 climate stations.

All the single-site input parameters (six parameters of the mixed gamma-Pareto distribution for non-zero precipitation and two parameters of the Gaussian distribution for the other variables) have been estimated for each of 528 stations of the dataset and for each of the 12 months separately. The RWG has been successfully tested and validated for the reproduction of daily and longer-term statistics of the six climatic variables at individual sites and the reproduction of the temporal and spatial pattern observed in the dataset. The validation results illustrate that the RWG is capable of generating long-term synthetic meteorological fields, capturing both regular and extreme events well. The detailed description of the implementation of the RWG would be extensive. Hence, for the sake of simplicity and balance of the paper structure, it will not be elaborated here. The readers are referred to Falter et al. (2015) for more details.

2.3.1.2. Rainfall-runoff model SWIM

The semi-distributed hydrological model SWIM (Soil and Water Integrated Model, Krysanova et al., 1998) simulates the hydrological cycle on a daily basis. SWIM uses three levels of spatial disaggregation: the river basin is divided into sub-basins which are further subdivided into hydrotopes. Water fluxes are computed at the hydrotope level, then aggregated on the sub-basin level. SWIM routes total runoff from sub-basin to sub-basin using the Muskingum routing method.

In this study, the Mulde catchment was divided into 77 sub-catchments based on Shuttle Radar Topography Mission digital elevation maps provided by the Federal Agency for Cartography and Geodesy in Germany (BKG). Hydrotopes were formed using soil and land use data from the soil map of Germany (BÜK 1000 N2.3) from Bundesanstalt für Geowissenschaften und Rohstoffe, the European Soil Database map from the European Commission's Land Management and Natural Hazards unit, and the CORINE (Coordinated Information on the Environment) land cover map.

To be able to assess the sensitivity of flood risk to the implementation of reservoirs, we added a reservoir component in SWIM. The specific operational strategy for each reservoir depends on a number of considerations. For example, after the disastrous flood in 2002, the storage reserved for flood retention has been increased at the expense of other purposes such as water supply for some reservoirs in Germany. The operational rules for reservoirs are expected to vary in time and from reservoir to reservoir based on local considerations. Further, it may be difficult to reconstruct them for reservoirs which have been in operation for decades. In this SWIM version, a simplified routine was integrated for simulating the retention effect of reservoirs automatically. Each modelled reservoir is linked to the sub-basin in which it is located and only the volume dedicated for flood control is implemented. When the flow at the sub-basin node exceeds the 100-year discharge (HQ_{100}), the streamflow beyond this threshold is stored in the reservoir, i.e. the hydrograph is cut at

HQ_{100}, as long as the required storage volume is available. When the flow falls below the threshold value of HQ_{100}, the reservoir starts releasing water so that the flow maintains the level of HQ_{100} as long as the active volume allows. If the storage capacity is filled before the inflow discharge falls below HQ_{100}, excess flow is routed downstream. Reservoirs operated in this way are very effective in reducing the peaks of extreme flood events. In total, 25 reservoirs (Fig. 2.1) within the Mulde catchment are integrated in the SWIM model set-up. The necessary information for reservoirs such as locations and flood storage capacities of reservoirs was adapted from Sächsisches Landesamt für Umwelt und Geologie (2002).

The new SWIM model set-up with reservoirs needed to be recalibrated and revalidated using the identical dataset, global optimization algorithm (SCE-UA, Duan et al., 1992) and objective function mNSE (based on the modified Nash-Sutcliffe efficiency measure giving more emphasis on higher flow) mentioned in Falter et al. (2015). The calibration and validation periods remain the same as well (calibration: from 1 January-1981 to 31-December-1989; validation: from 1-January-1951 to 31-December-2003 excluding the calibration period). The calibration and validation results illustrate an improvement in this new model set-up compared to the version used in Falter et al. (2015). At the upstream station Lichtenwalde, Nash-Sutcliffe efficiency (NSE) values of 0.81 (calibration) and 0.83 (validation) are achieved for the new set-up against 0.77 and 0.81 for the old one. At the downstream Mulde station Bad Düben, the corresponding values are 0.89 and 0.86 against 0.89 and 0.83. Overall, a modest difference in model performance between the two model set-ups is found looking at the obtained NSE values and the plots in Fig. 2.3. However, with the new set-up, the SWIM model is able to represent the cut-off process of the extreme flood events due to the implementation of reservoirs. The modelled peak flow of the August 2002 flood fits well to the observed peak flow (Fig. 2.3).

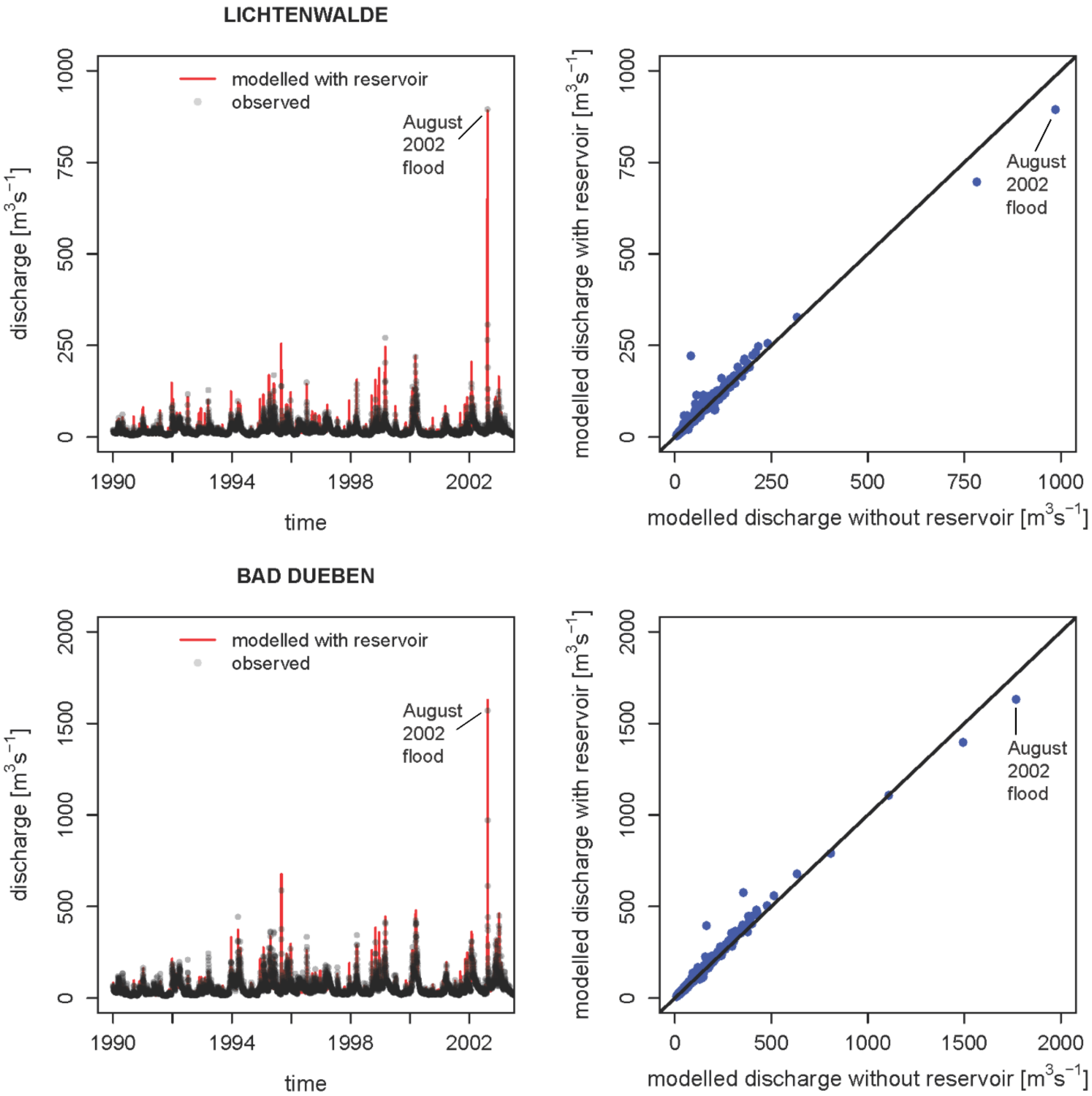

Figure 2.3: Model performance of SWIM at selected gauging stations.

2.3.1.3. Regional inundation model RIM

With the hydrological routing, SWIM calculates wave propagation without explicit consideration of the river channel geometry. However, to predict dike overtopping and simulation of hinterland inundation, water level information along the river network is needed which is provided by the Regional Inundation Model (RIM). It consists of a 1-D hydrodynamic channel routing model for the domain between river dikes and a 2-D hydrodynamic inundation model for the dike hinterland. Both models are coupled, i.e. the 1-D model gives the overtopping flow as a boundary condition to the 2-D model, and the hinterland water levels computed by the 2-D model are used as boundary conditions for the 1-D model. The channel routing model solves the 1-D diffusive wave equation using an explicit finite difference solution scheme and it simulates only the flood flows exceeding the bankfull discharge. To this end, the river cross-section geometry was simplified including the overbank river geometry and the elevation of flood protection dikes.

Whenever the water level reaches the dike crest level, overtopping flow into the hinterland is calculated using the broad-crested weir equation. Hinterland inundation processes are simulated with a 2-D raster-based model based on the inertia implementation of Bates et al. (2010). The 2-D inundation model was implemented in CUDA Fortran on graphical processor units to increase the computational speed.

River cross-section profiles, dike heights and locations, and Manning's roughness values are necessary for setting up the 1-D model. The main data source for the geometric characteristics is the 10 m resolution digital elevation model (DEM) supplied by the BKG. Additionally, information on channel width and dike location was obtained from the digital basic landscape model (Base DLM) provided by BKG. The river profiles were manually extracted perpendicular to the flow direction with about 500 m in spacing. Since the resolution of DEM 10 m tends to provide too low of dike heights and additional dike information is not available, a threshold was introduced as a global correction value for the minimum dike height. Following the study of Falter et al. (2015), the minimum height was assumed to be 1.8 m. The Manning's coefficient of $n=0.03$ was adopted constant over the entire river network. The 2-D raster-based model uses a 100 m resampled computational grid from DEM 10 m, which was found to be an acceptable compromise for representation of inundation characteristics and computation time (Falter et al., 2013).

Falter et al. (2015) validated the 1-D hydrodynamic model at five gauging stations (Fig.2.1) in the Mulde catchment with observed data over the period 1951-2003. Although there was a tendency to underestimate the number of observed peak flows exceeding the bankfull depth, the general performance was acceptable. Validation of hinterland inundation is harder due to the lack of information about inundation depth and extent. In our study area, observed inundation is only available for the extreme flood of August 2002, provided by the German Aerospace Center (DLR). While inundation areas are simulated well for the eastern tributary Freiberger Mulde, only around 50% of the flood extent is correctly simulated for the entire catchment due to neglected dike breaches in the model chain. Although there is an underestimation of inundation extents, the model is suitable to assess changes in risk for the mesoscale Mulde catchment. The actual damage estimates for the catchment area are not primarily targeted for this study. Details can be found in Falter et al. (2015).

2.3.1.4. Flood Loss Estimation Model FLEMOps

The Flood Loss Estimation Model for the private sector (FLEMOps) is used to calculate direct economic damage to residential buildings for each inundation event using the maximum water level information provided by RIM. The base version of FLEMOps uses five inundation depth classes, three building types, two building quality classes, three water contamination classes, and three private precaution classes as inputs (Thieken et al., 2008). Due to the fact that less damage occurs if people are regularly affected by flood, the advanced version additionally considers the return period of the inundation at the flooded buildings as damage-influencing factor (Elmer et al., 2010, 2012). FLEMOps provides the damage ratio, i.e. the relative damage. The monetary damage is calculated by multiplying the damage ratio with the asset values of the exposed elements.

FLEMOps uses spatially detailed information about asset values, building types, and building quality. All gridded input data were resampled to 100 m spatial resolution. The damage calculation is carried out for 100×100 m^2 cells and then aggregated to the level of municipalities. Asset values of the regional stock of residential buildings were characterized considering standard construction costs (BMVBW, 2005). These asset values were spatially distributed according to the CORINE land cover classes 111 (continuous urban fabric) and 112 (discontinuous urban fabric). Municipal-scale information on building type and quality was provided by Infas Geodaten GmbH (2009). The composition of building types is defined using a cluster centre approach. In total five clusters are defined differentiating the share of single-family houses, semi-detached/detached houses, and multi-family houses. Average building quality is aggregated to two classes: high quality and medium/low quality (Thieken et al., 2008). The flooding impact is characterised by inundation depth and return period of peak flows. The latter is calculated at the SWIM sub-basin level by fitting a generalized extreme value distribution to the annual maximum discharge series obtained from 4000 years of continuous SWIM simulation. In addition to inundation depth, return period, building type, and quality, contamination (none, medium and heavy) and private precaution (none, good and very good) are also taken into account in the damage model. The overall effect of contamination and private precaution is quantified by scaling factors. Building type and quality are assessed on municipality level; further municipal asset data are disaggregated with the help of a dasymetric mapping approach. Loss estimation is carried out on a raster level by determining loss ratio by the inundation depth in that cell and the underlying municipality which is linked to a building types and quality (Thieken et al., 2008).

The flood loss estimation was evaluated by Falter et al. (2015) for the 19 affected communities in the state of Saxony in Germany during the flood event of August 2002. The sum of damages to residential buildings for all communities was officially reported as EUR 240 million, and it was calculated as EUR 67 million from the model chain. The simulated affected residential areas match about 30% of the observed affected residential areas. This underestimation may be explained by uncertainty in asset values and their spatial distribution, the differences in simulated and observed inundation patterns, and uncertainty in the damage model. For details we refer to Falter et al. (2015). In the current model set-up with reservoir implementation, the calculated damage value is smaller, about EUR 61 million. That is because the inundation depth at some locations is slightly decreased in the set-up with reservoirs, although simulated affected residential areas in the two set-ups are similar for the flood event August 2002.

2.3.2. Sensitivity analysis

2.3.2.1. Outline of the sensitivity analysis

We investigate the sensitivity of risk to changes in the flood risk chain components. To represent the entire flood risk chain, we analyse the effects of changes in the following six components: atmosphere (A), catchment (C), river system (R), exposure related to land use (EL), exposure related to asset values (EA), and vulnerability (V).

The most comprehensive approach for understanding model sensitivity is global sensitivity analysis in which regression methods, screening-based, variance-based and meta-modelling approaches are widely used (van Griensven et al., 2006; Pianosi et al., 2016; Song et al., 2015). Global sensitivity analysis evaluates the effects of all input parameters and their combinations on the output based on a large number of model runs. However, this approach cannot be combined with the derived flood risk analysis based on continuous simulation in our case study due to the massive computational time that would be required. Therefore, we use a much less demanding approach, the logic tree approach, to identify the contribution of each component to changes in flood risk and to understand interaction effects by analysing all possible combinations.

For each component, we limit the sensitivity analysis to three scenarios, a baseline scenario and two symmetric change scenarios. The baseline scenario represents the current state. The change scenarios represent plausible deviations from the baseline. This set-up leads to 729 (3^6) scenarios. The combinations of six components are shown in Fig. 2.4.

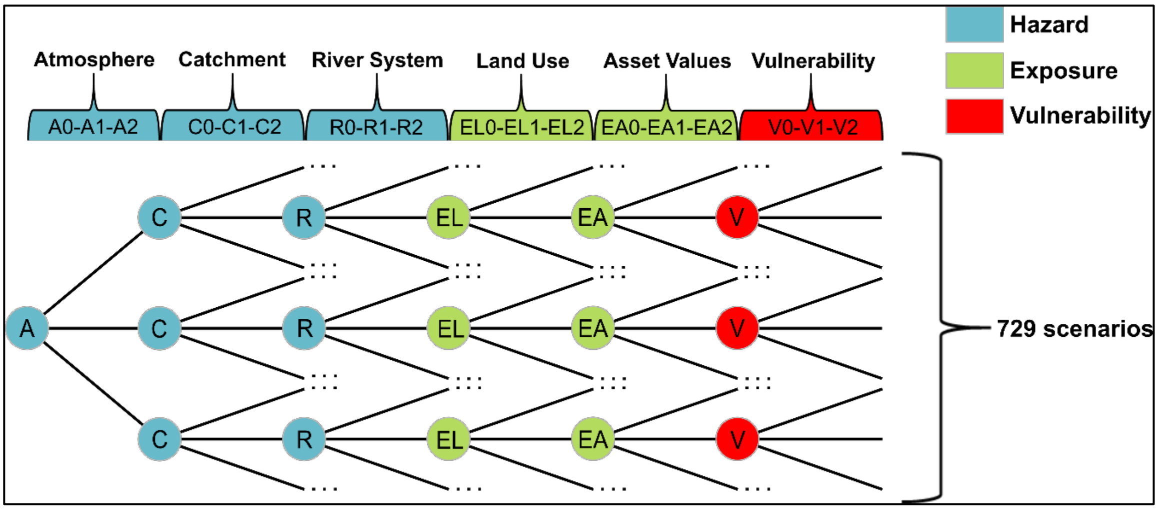

Figure 2.4: Conceptual scheme of combinations for six components (atmosphere, catchment, river system, land use, asset values and vulnerability). For each component, there is one baseline (denoted by 1) and two symmetric change scenarios (denoted by 0 and 2).

The variables that are changed for each component and their values for the baseline and change scenarios are described in the following sections and summarized in Table 2.2. It has to be noted that for a given component different types of changes would be possible. We have focussed our analysis on those types of changes that we consider most important for flooding in our study region. For example, changes in catchment hydrology are represented by changes in reservoir storage. Other changes, such as changes in agricultural practice possibly leading to changes in infiltration behaviour and runoff coefficients, are not considered. Further, the amount of change assumed for each component reflects another subjective choice. Finally, it should be noted that the change scenarios do not necessarily change the flood risk in the same direction. For example, scenario 2 of the catchment component represents increased flood retention capacity and hence reduced flood risk.

Conversely, scenario 2 of the vulnerability component assumes lower precaution compared to the baseline scenario and hence higher flood risk.
Each of the 729 scenarios consists of a continuous, spatially distributed simulation of the entire risk chain for 4000 years. From these resulting space-time fields of damage two risk indicators are analysed, namely the risk curve and the expected annual damage (EAD). The risk curve is obtained by plotting losses against their probability of occurrence. EAD is calculated by integrating over the risk curve. In this paper, we provide the results in aggregated form for the complete Mulde catchment, although the spatially explicit modelling set-up allows the derivation of the sensitivity for each sub-catchment.

2.3.2.2. Change in climate

For the baseline scenario, the weather generator is calibrated using observation data from 1951 to 2003. We defined two plausible change scenarios considering seasonally different changes in precipitation and temperature. To apply these changes to the precipitation and temperature time series of the baseline scenario, we used the delta change method. For precipitation, the baseline time series of 4000 years of daily precipitation was multiplied by a change factor. For temperature, the change factor was added to the daily temperature time series of the baseline scenario (Table 2.2). The change factors were derived from observed changes in mean seasonal precipitation and temperature across Germany and are roughly representative for the past 50 years (Umweltbundesamt 2017a, b). Scenario A2 represents a warmer climate and A0 a colder climate.

2.3.2.3. Change in catchment hydrology

Flood generation may be affected by a variety of mechanisms. Examples are land use changes, such as conversion of agricultural areas into settlements or changes in infiltration behavior due to soil compaction as consequence of more heavy machinery. We limit our analysis to changes in flood retention storage in reservoirs, which we consider to be the most important influence for the catchment component. Flood control by reservoirs is one of the dominant flood risk management strategies in Germany. In upstream sub-basins of the Mulde catchment, a flood retention capacity of around 106 million m^3 has been implemented from 1825 to 2001 by constructing 25 reservoirs.

The baseline scenario C1 considers these 25 reservoirs. They were integrated into SWIM at their locations shown in Fig. 2.1. As change scenarios, we consider the catchment without reservoirs (scenario C0) and with double storage capacity (scenario C2). In the latter case, we doubled the storage volume for each of the 25 reservoirs at the respective sub-basin.

Table 2.2: Baseline and change scenarios for the sensitivity analysis. For each component the variables that are changed in the sensitivity analysis and their scenario values (S1: baseline; S0, S2: change scenarios) are given.

Component	**Variable**	**Scenario values (S0 / S1 / S2)**	**Explanation**
Atmosphere (A)	Precipitation [mm]	Winter: (-19.0 / 0 /+19.0) Spring: (-8.1 /0/+8.1) Summer: (+1.1/ 0 / -1.1) Autumn: (-5.9 / 0 /+5.9)	Daily precipitation is multiplied by change factor $(1+\Delta_p/\overline{p^0})$ where $\overline{p^0}$ is the mean precipitation amount for the baseline scenario series and Δ_p is the seasonal change in mean precipitation over the 50 years period. Δ_p values are given in the third column.
	Temperature [°C]	Winter: (-0.49 / 0 / +0.49) Spring: (-0.45 / 0 / +0.45) Summer: (-0.45 / 0 / +0.45) Autumn: (-0.38 / 0 / +0.38)	Change in mean temperature over the 50 years is added to daily temperature value on seasonal basis.
Catchment (C)	Reservoir capacity [Mio m^3]	0 / 106 / 212	Current capacity is doubled and completely removed.
River system (R)	Dike height [m]	(-0.5 m / 0 / +0.5 m)	Current dike height is changed by 0.5 m.
Land use (EL)	Residential area [km^2]	560 / 672 / 784	Current residential land use area is changed by 112 km^2.
Value of assets (EA)	Building price index	0.66 / 1 / 1.34	Current index is changed by 34 %.
Vulnerability (V)	Scaling factor of relative damage	0.71 / 0.95 / 1.20	Scaling factor of medium level precaution is increased and decreased by 26 %, for the cases of no precautionary measure and high precaution level, respectively.

2.3.2.4. Changes in the river system

For the river system, we focus on the effects of dikes on flood risk because dikes are the most extensively used flood protection measure along rivers in Germany. The baseline scenario R1 represents the current situation with the existing dikes.
To create change scenarios, we needed to define reasonable changes in dike height. The current height was decreased (scenario R0) and increased (scenario R2) by 0.5 m. This increment is based on studies about potential dike heightening in the Netherlands. Zwaneveld and Verweij (2014) considered 0.6 m dike heightening, and Hoekstra and Kok (2008) compared two dike-heightening strategies and for the better performing approach they assumed dike heightening in the range of 0.48 m to 0.71 m.

2.3.2.5. Land use change

Since the flood risk model chain used in this study considers only damage to private households, we limit the effect of land use change to residential areas. The baseline scenario (EL1) considers the CORINE land cover classes 111 (continuous urban fabric) and 112 (discontinuous urban fabric) for the year 2012. Land use change scenarios were created based on increase in residential areas between the years 1990 and 2012 by randomly changing the state of single pixels. The change scenario EL2 is based on the increase in area of two land cover classes from 672 to 784 km^2 between 1990 and 2012 for which the change area was added to baseline scenario. To obtain the symmetric change scenario EL0, the same change in area (112 km^2) was subtracted from the situation in 2012. Pixels (100 x 100 m^2) of the classes 111 and 112 were assigned to residential land cover classes and all other classes were assigned to non-residential land cover classes (i.e. agricultural areas and semi-natural areas).

2.3.2.6. Change in asset values

For the baseline scenario (EA1), the building values from Kleist et al. (2006) for the year 2000 were converted to 2012 to be consistent with the baseline land use map. This conversion was based on the building price index (BPI), which represents the growth in construction prices compared to a reference year for Germany (Baupreisindex-BPI, DESTATIS, 2012). In agreement with the change scenarios for land use, we generated the change scenarios for asset values by scaling the baseline scenario with the relative change in BPI between 1990 and 2012. Hence, the change scenario EA2 represents a situation with a 34 % increase in asset values, and EA0 represents a 34 % decrease compared to EA1.

2.3.2.7. Change in vulnerability

Vulnerability of private households is influenced by a variety of dimensions such as social, economic and institutional, and it is challenging to quantify the relation between these dimensions and the damage ratio (Merz et al., 2010a). Therefore, in the present study, we focus on the economic dimension of vulnerability. To represent changes in vulnerability, we use FLEMOps, which was derived from comprehensive surveys of flood damage in

Germany (Thieken et al., 2008, Elmer et al., 2010). These surveys show that, in addition to flood and building characteristics, contamination and precaution are significant factors in determining the damage. Since contamination is in many cases imposed externally on households, for example by contamination through sewage water, we focus our analysis on the effects of precaution.

The three vulnerability scenarios are defined by scaling the relative damage according to the level of precaution at the household level. For medium contamination, the scaling factors are 1.20 and 0.71 for 'no precautionary measures' and 'very good precautionary measures', respectively (Büchele et al., 2006). Hence, the change scenario V2 with a scaling factor of 1.20 represents a situation without precautionary measures, and V0 a situation with very good precaution (scaling factor 0.71). To obtain symmetrical changes, the scaling factor of the baseline scenario V1 is set to 0.95.

2.4. Results

2.4.1. Sensitivity of flood risk at the catchment scale

The impact of each component on flood risk is illustrated in Figure 2.5 in terms of EAD, aggregated to the whole Mulde catchment. Changes in each risk component are represented by three box plots, whereas each box plot is derived from 243 scenarios for the change scenario 0, 1 and 2 of that risk components.

One of the most striking results is observed for the change in the river system. The median values for different dike heights are EUR 1.2 million, 0.8 million, and 0.3 million for scenarios 0, 1 and 2, respectively. Hence, there is a very strong reduction in EAD with dike heightening. The maximum EAD value for the high-dike scenario is EUR 1.1 million which is very low compared to the EAD values obtained across all scenarios. Another remarkable result is the rather small increase in the median values for changes in the atmosphere (A) from scenarios 0 to 2 (from EUR 0.6 million to 0.8 million), despite the realistic assumptions on average changes in climate variables. This result indicates that changes in climate might not be the dominant ones along the risk chain, contrary to the prevailing perception. Although our model does not capture complex change patterns such as changes in duration of wet spells or clustering of events, we believe this would not dramatically change the magnitude of climate-induced changes. For the catchment (C) component, the median value for scenarios without a storage capacity (C0) is EUR 1 million, while it is around EUR 0.6 million for scenarios with both baseline storage capacity and double storage capacity. This non-symmetry in the effects of the catchment component is explained by the specific implementation of the reservoir capacity: implementing a capacity of 106 million m^3 reduces the EAD significantly, but doubling this reservoir capacity at the same locations does not further reduce the risk substantially because the reservoir capacity in the baseline scenario is already sufficient to capture floods above HQ_{100}. For changes in land use (EL) and in vulnerability (V), median values of EAD increase from scenarios 0 to 2 (from EUR 0.5 million to 0.9 million). Similar increases are obtained for the component asset values (EA). These results imply that the assumed changes in land use, asset values and vulnerability have considerable impacts on flood risk, only topped by the change in dike heights.

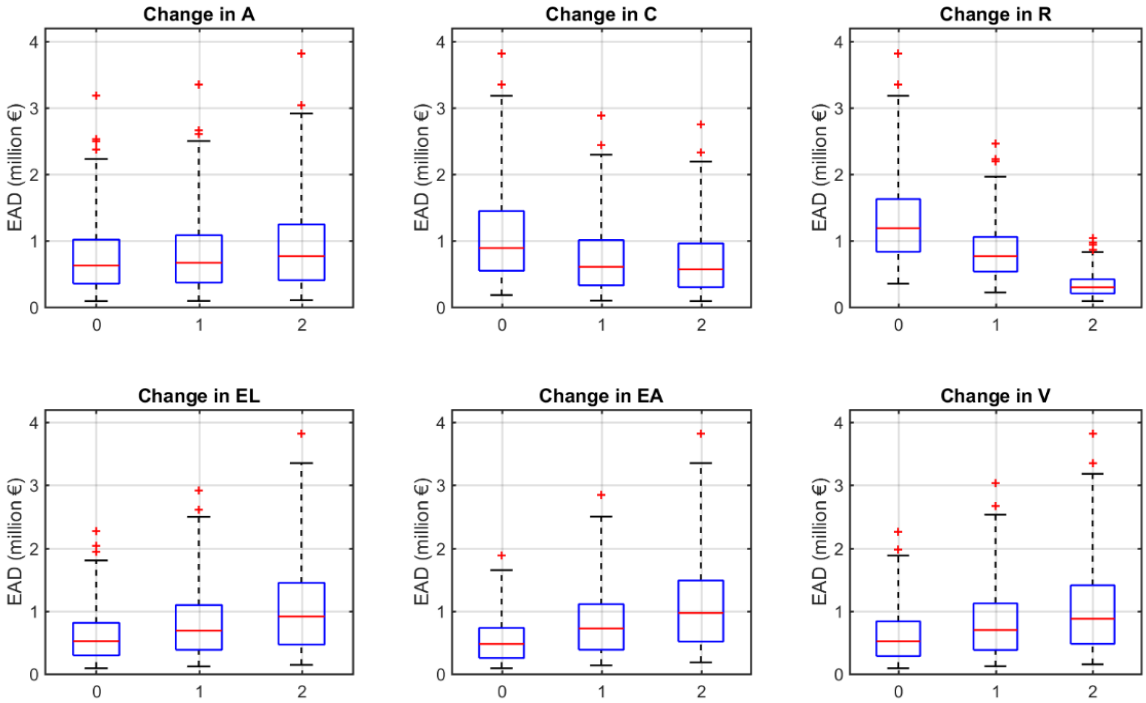

Figure 2.5: Box plots of EAD, aggregated at the catchment scale, for changes in six components: atmosphere (A), catchment (C), river system (R), land use (EL), asset values (EA), and vulnerability (V). The box plots show the median values (red lines), the 25th and 75th percentiles (top and bottom of boxes) and the range (whiskers). Outliers are shown by "+".

Figure 2.6 shows the effects of the different components on the risk curve. This representation illustrates the effect of changes in risk components across the whole spectrum of probabilities, whereas the EAD gives aggregated information. For each component, the baseline scenario is compared to the two symmetric scenarios, whereas only the respective component is changed and all other components are fixed at their baseline state. The upper left plot of Fig. 2.6 shows the effect of change in the atmosphere (A). Differences among the risk curves are only visible for high-probability events, whereas for extreme events the risk curves are similar for different climate scenarios. This is explained by the interplay of the flood regime in the Mulde catchment and the seasonal variations applied in the climate change scenarios. Most of the floods occur in winter; however, the most extreme events tend to occur in summer. Since the change scenarios, based on past observations, assume a strong increase in precipitation in winter and almost no change in summer (see Table 2.2), climate change manifests itself mainly for high-probability events.

Changes in catchment (C) have the opposite effect on the risk curves, i.e. they affect only low-probability events. This is a consequence of the threshold process applied in the reservoir implementation in which the 100-year discharge (HQ_{100}) is used to cut off the extreme flood flow. The reduction in EAD is modest compared to the effect of other components, such as dike heightening. This can be explained by the small contribution of extreme events to EAD. Merz et al. (2009) have shown that EAD is dominated by "high probability-low damage" events and that "low probability-high damage" events play a small role, because their low probabilities overcompensate their high damages. They have further argued that extreme events are more important for the affected societies than is expressed by their contribution to EAD. Hence, EAD is rather insensitive to changes in reservoir capacity in our case study, and the use of EAD as risk indicator might undervalue the risk-reducing effect of reservoirs. This discussion also provides a note of caution on a higher level: the relative contribution of different components to changes in risk varies across the probability spectrum, and changes that affect mainly low-probability events may be undervalued by EAD which has been used almost exclusively in the studies to date (Table 2.1).

Changes in the river system (R) and in land use (EL) have a substantial impact across the whole probability spectrum, whereas the impact of changes on asset values (EA) and on vulnerability (V) tends to increase from high-probability to low-probability events.

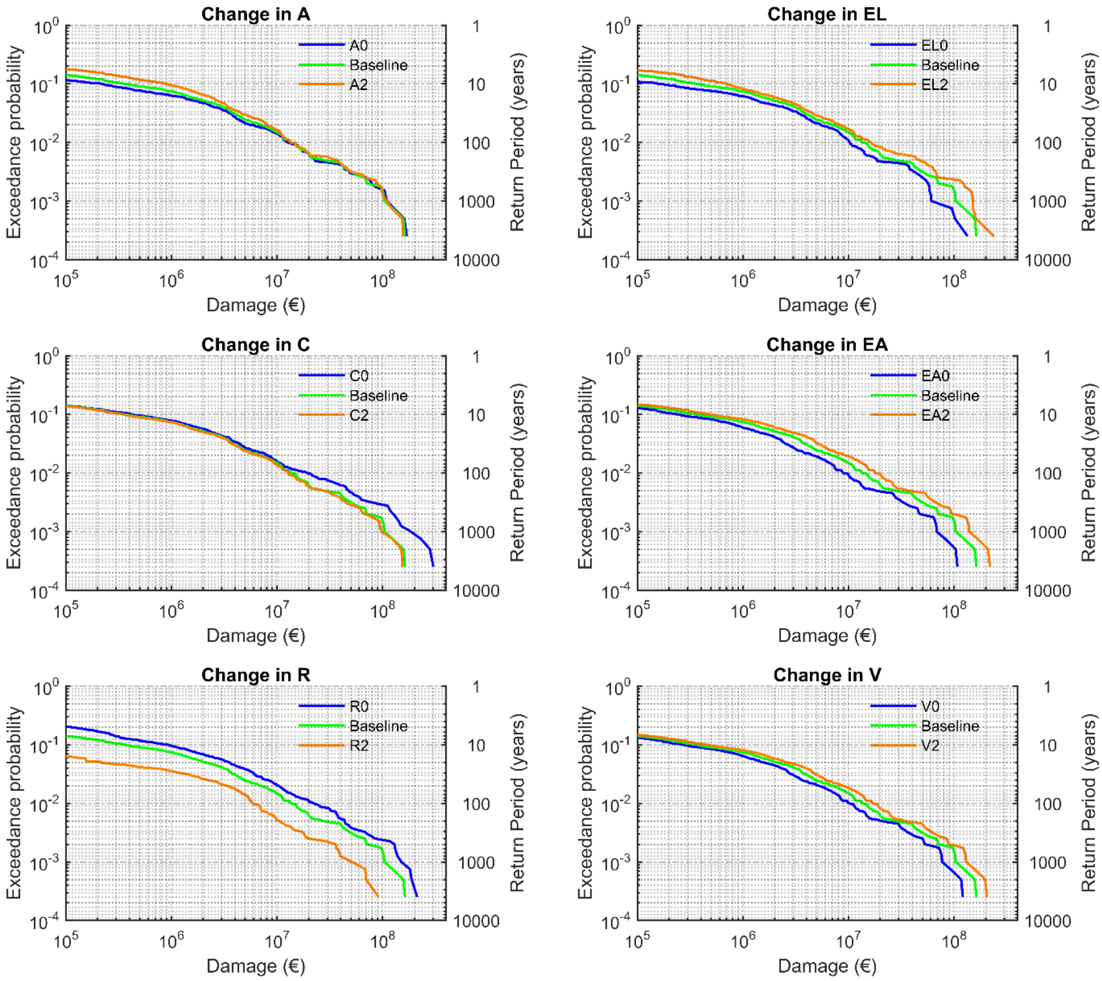

Figure 2.6: Risk curves, for damages aggregated to the catchment scale, for changes in six components: atmosphere (A), catchment (C), river system (R), land use (EL), asset values (EA) and vulnerability (V) under baseline conditions. Baseline represents baseline scenarios for each component, which is denoted by A1C1R1EL1EA1V1. All change scenarios vary only in the respective component. For example, A0 means A0C1R1EL1EA1V1.

2.4.2. Sensitivity of flood risk for selected upstream and downstream locations

To get a better understanding of changes in risk and of their spatial heterogeneity within the catchment, two districts located upstream (Zwickau) and downstream (Anhalt-Bitterfeld) in the catchment are analysed in more detail. Their risk curves for changes in the six components, compared to the baseline, are given in Fig. 2.7. The change in the atmospheric component (A) shows a behaviour in these two sub-basins similar to in the whole catchment. Regarding the change in catchment hydrology (C), change in flood storage capacity has a more dominant impact upstream, which is explained by the reservoir locations (see Fig. 2.1). The (upstream) reach around Zwickau is directly downstream of a large reservoir. However, doubling the capacity of this reservoir does not result in risk changes. At the downstream region influenced by several river branches, aggregated impact from various reservoirs upstream is observed. It seems that for very large events doubling of reservoir capacity still exerts a small impact on the risk downstream. Change in river system (R) strongly impacts risk both upstream and downstream. While the difference between scenarios with low dike height (R0) and baseline dike height (R1) is small upstream, there is a significant difference in the risk curves between these scenarios at the downstream location for high probability events. One potential reason for this is the influence of topography on the number of exposed asset values. It is likely that under the assumption of equal value per exposed asset unit, steep upstream and flat downstream reaches are affected differently by the same flood magnitudes. In flat downstream areas changes in dike heights result in great differences of damage values since more assets are flooded. From the risk curves of different land use scenarios, it should be noted that the increased urban area scenario (EL2) increases risk upstream for high-probability events and downstream for low-probability events. The difference between EL0 and EL2 scenarios is high upstream for high-probability events because reservoirs do not affect flows below the 100-year discharge. When they start to operate, risk for different land use scenarios becomes similar. However, the baseline land use scenario (EL1) and the EL2 scenario behave almost identical upstream, which depends on the rules adopted for increasing the urban area and changes in the flood extent for different return periods. It can also be explained by the steep topography in which the additional residential buildings for the EL2 scenario might be located at steeper areas, and thus they are not exposed to floods. Conversely, the difference between the risk curves of EL1 and EL2 is high for extreme events at the downstream location. Risk curves of EL0 and EL1 scenarios are almost identical downstream. Similar to the identical behaviour of the EL1 and EL2 scenarios upstream, this can be explained by the specific set-up of the residential buildings added in EL1, which are not exposed to floods. The last two components, change in asset values (EA) and vulnerability (V), have a similar impact on the risk curves at both upstream and downstream locations.

For the downstream district, abrupt (vertical) changes in the risk curves are observed around 500-year or greater return period events. In fact, events around this abrupt change have different peaks corresponding to different return periods but they show similar flood volumes. Therefore, they result in similar inundation depths and similar damage values for different probabilities.

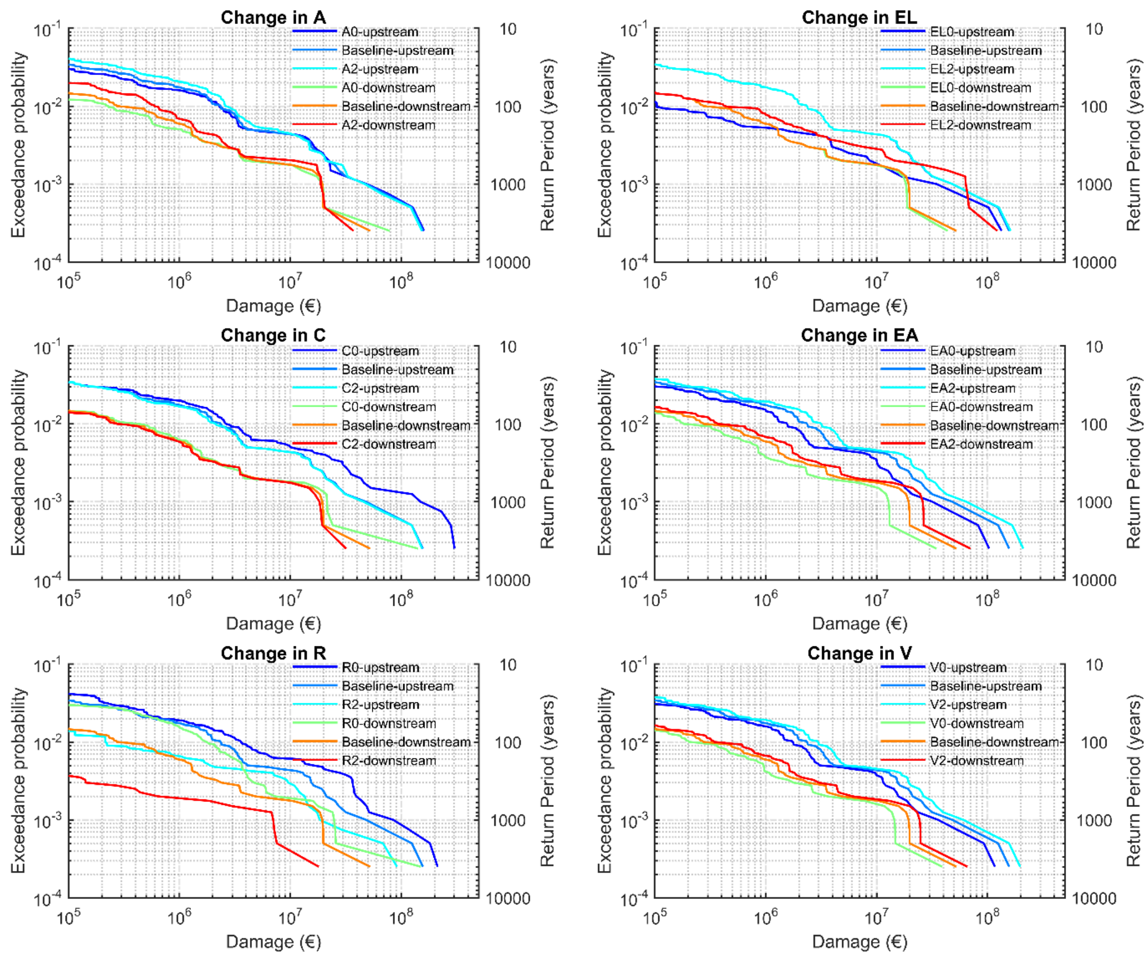

Figure 2.7: Risk curves for changes in six components: atmosphere (A), catchment (C), river system (R), land use (EL), asset values (EA), and vulnerability (V), under baseline conditions at districts Zwickau (upstream) and Anhalt-Bitterfeld (downstream).

2.4.3 Seasonal effects on changes in risk curves

To understand the temporal pattern of changes in risk, risk curves for summer and winter seasons are illustrated in Fig. 2.8. Only the results for the atmosphere, catchment, and river system components are shown because they directly affect the peak flows in different seasons. It can be concluded that events in the summer season cause higher losses for the same return periods. We can observe different sensitivities in the winter and summer seasons. First, for change in atmosphere (A), differences among change scenarios are observed throughout the whole probability range in the winter season. In summer, changes are very small. This is related to the much larger variation in precipitation values in winter compared to summer (Table 2.2). Second, change in catchment system (C) affects the risk curve for events with return periods higher than 500 years in winter, while differences can be observed already for the 100-year event in summer. This can be explained by the reservoir operation rule and the magnitude of events in different seasons. For example, the 100-year event in summer and the 800-year event in winter are of a similar magnitude corresponding to the 100-year flood of the annual time series, which is the threshold for reservoir operation. Finally, differences in risk curves across the whole probability range are visible for change in river system (R) for both seasons.

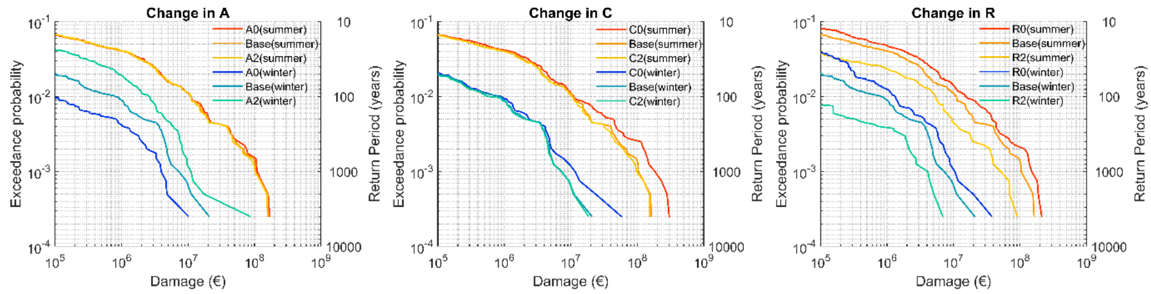

Figure 2.8: Risk curves for changes in three components, atmosphere (A), catchment system (C), and river system (R), under the baseline conditions for winter (blue colours) and summer (red colours).

2.4.4. Relative influences of different components on flood risk

For a better visualization of the combined or opposed effects of different risk components on EAD, parallel-coordinate plots are used in Figure 2.9-2.11. These plots consist of seven parallel axes whereas the first six axes represent the different risk components, i.e. from left to right, changes in atmosphere (A), catchment system (C), river system (R), land use (EL), assets (EA), and vulnerability (V). The seventh axis shows EAD obtained from different combinations of risk components: the scenarios are indicated by 0, 1 and 2 on the parallel coordinates, and each combination of components is represented by a different colour. In this way, combinations of risk components that result in a certain EAD interval are easily visualized.

In Fig. 2.9 a subset of change scenarios is highlighted that results in very high EAD values above EUR 2.5 million. It is interesting to note that all these scenarios contain the low-dike height scenario (R0). As soon as another river system scenario (R1 and R2) is selected, EAD falls below EUR 2.5 million. Increasing the dike height seems to be the most effective measure to keep the damage below a predefined threshold irrespective of changes in other risk components.

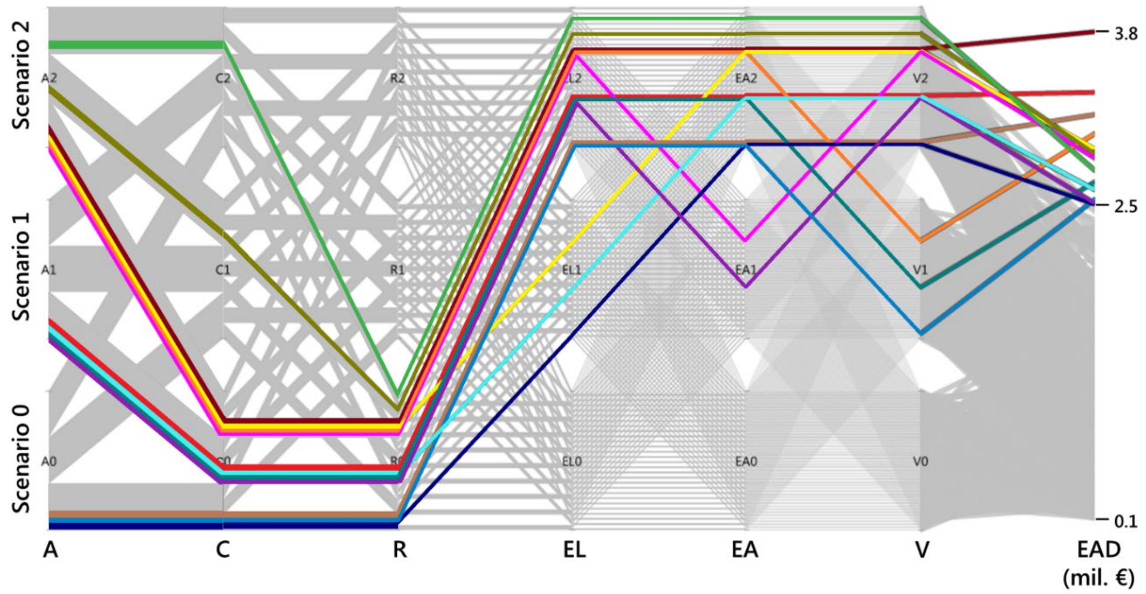

Figure 2.9. Parallel-coordinates plot showing combinations of flood risk components that result in a certain EAD interval. From left to right, the six parallel coordinates represent changes in the flood risk components (A, C, R, EL, EA and V), and parallel coordinate on the right-hand side shows EAD (million EUR) obtained from different combinations of risk component scenarios. Change scenarios are indicated by 0, 1 and 2 on the parallel coordinates. Each highlighted scenario is represented by a different colour.

In order to understand the impact of climate change on EAD, the baseline scenario for all components and six different combinations with a warmer climate scenario (A2) are analyzed (Fig. 2.10). Particularly, we looked which other components can offset the effect of the atmospheric component. Under the fixed A2 scenario, five scenario combinations are highlighted, each time altering a different component from its baseline value. For instance, in order to understand the relation between atmosphere and catchment changes, we compared the baseline scenario and the scenario of a warmer climate and increased storage capacity ($A2C2_1$), for which subscript 1 denotes that all other components are kept in their baseline state. Scenario $A2C2_1$ causes an increase in EAD compared to the baseline EAD value, meaning that climate change has a more dominant impact than catchment changes. Consequently, one could argue that changes in catchment system cannot compensate for the impact of climate change under the selected assumptions. In the case of river system changes, the $A2R2_1$ scenario decreases EAD to the value of EUR 0.3 million, compared to the baseline scenario of EUR 0.7 million. Hence, increased dikes can offset the adverse effect of the warming climate on flood risk. Changes in land use, asset values and vulnerability ($A2EL0_1$ $A2EA0_1$, $A2V0_1$) result in EAD below the baseline scenario, thus compensating for the effect of climatic changes.

To compensate for the adverse effects of climatic changes, management options in all other risk chain components can be adopted. They are, however, associated with different implementation costs, a different degree of feasibility, or varying public acceptance. For instance, increase in dike heights along extended river networks can be very costly.

Construction of additional reservoirs might adversely affect the ecological state of the river or be simply not feasible. We thus explored the set of scenarios, in which changes in the catchment and river systems were kept constant. Asset values were kept at the baseline level or were allowed to increase. By changing the land use and vulnerability values, the EAD was retained in the range from EUR 0.5 million to 2 million (Fig. 2.11). Under these assumptions, it is possible to restrain the effect of climate change and increasing asset values on flood risk without implementing technical flood protection measures.

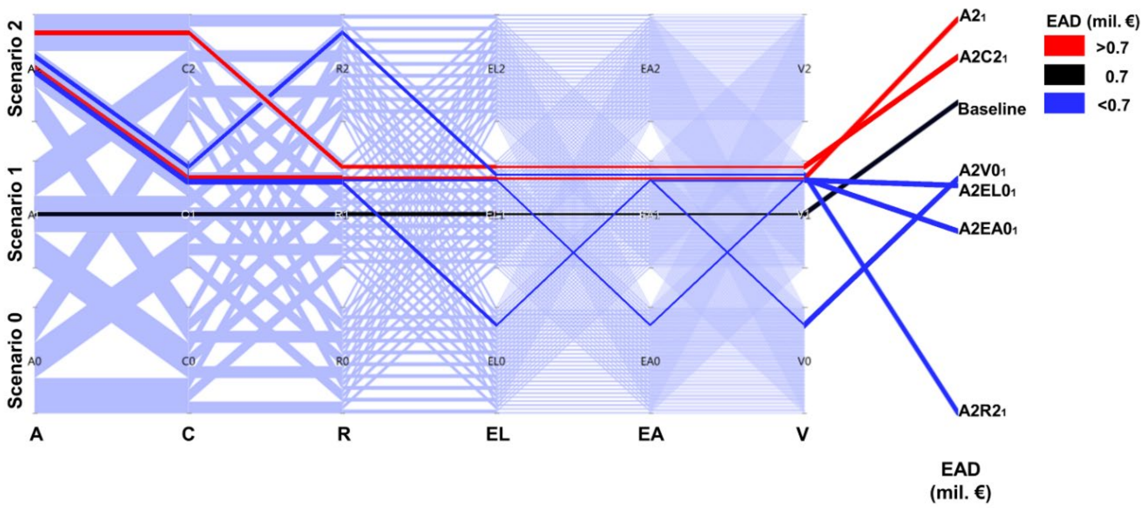

Figure 2.10: Parallel-coordinates plot representing the baseline scenario (Scenario 1) for all components and six combinations of flood risk components with warmer climate scenario (A2): $A2_1$, $A2C2_1$, $A2R2_1$, $A2EL0_1$, $A2EA0_1$, and $A2V0_1$ where subscript '1' shows that all other unwritten components are in their baseline condition.

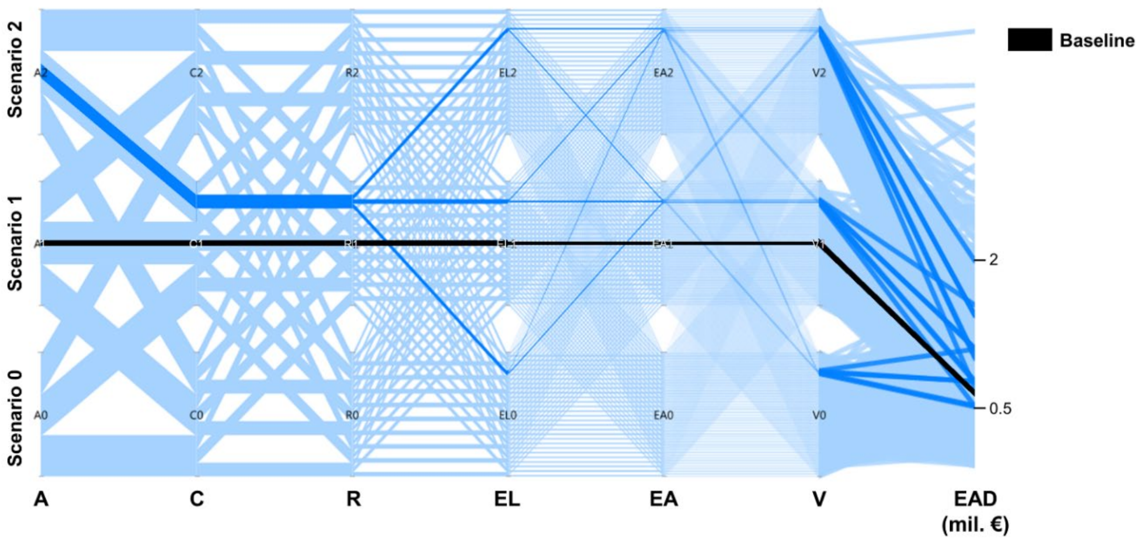

Figure 2.11: Parallel-coordinates plot representing EAD for change in land use (EL) and vulnerability (V) under fixed baseline catchment and river system scenarios and increasing atmosphere and asset values.

2.5. Discussion

The main purpose of this study is to fill the research gap on changes in flood risk, for which consideration of the entire risk chain is generally missing. Taking into account all risk components allowed us to explore the effect of changes in the individual risk chain components and their mutual interactions.

To the authors' knowledge, this study is the most comprehensive analysis on the influences of different drivers of flood risk, including hazard, exposure and vulnerability drivers. The combination of sensitivity analysis with the DFRA approach overcomes a number of limitations of event-based risk assessments. Although our change scenarios have subjective assumptions, we used the best available data and options to create these scenarios. The expected annual damage reaches a maximum of EUR 4 million in our case, and for extreme events we obtain maximum absolute losses of around EUR 100 million. For extreme events, changes in all risk components, except in the atmospheric component, have an impact on the damage. The impact of climate change is mostly visible for high-probability flood events. This was explained by seasonal variations in precipitation change between scenarios in combination with the specific flood regime of the Mulde catchment.

The presented results are subject to limitations related to the flood risk chain model and the subjective assumptions for the reasonable change scenarios. Each model along the risk chain has limitations and uncertainties. For instance, water level calculation in the 1-D hydrodynamic model strongly depends on river geometry estimated by the simplified river cross sections. Neglected dike breaches (only overflow is considered) are another limitation in the representation of hydraulic processes. Further, flood damage estimation is sensitive to inundated areas and exposed assets, both based on coarse DEMs. High uncertainties also pertain to flood damage modelling; they can have a larger contribution to uncertainties in risk estimates than uncertainties in hydrological and hydraulic components (Apel et al., 2009; de Moel and Aerts, 2011; Vorogushyn et al., 2012). More detailed discussion on limitations of the flood risk model chain can be found in Falter et al. (2016).

The impact on flood risk highly depends on the defined change scenarios of the risk components. In the sensitivity analysis, there is some subjectiveness in their selection. The assumed change amounts for each component and the methods to create plausible change scenarios reflect different subjective choices. For instance, the climate change scenarios were generated based on observed past changes. Due to anthropogenic climate change, the effects on temperature and precipitation will likely be different. However, in order to explore the effect of reasonable changes in climate on flood risk, we consider this assumption acceptable, as this study does not attempt to evaluate flood risk under various climate projections available to date. In the catchment change scenarios, we used large changes such as doubling the reservoir storage capacity. Yet, we observed comparatively small effects for the particular case study area given the implemented operation rules. Scenarios for river system were determined based on possible changes in dike heights adopted from the literature. Conditional on our assumptions, change in dike height is able to compensate for the risk-increasing impact of other components. In the land use change scenarios, the selection of the time period as well as the spatial distribution of changes in individual pixels is obviously subjective. The latter can potentially be overcome by considering multiple scenarios of spatial distribution of changes in pixel state in relation to distance to the river and thus propensity for inundation. In the vulnerability scenarios, we only focused on the impact of private precautionary measures. Other aspects, such as awareness and preparedness, can also alter vulnerability. However, between the disastrous floods in 2002 and 2013 in Germany, private households and companies substantially adopted precautionary measures (Kreibich et al., 2017). Therefore, our scenarios are reasonable to represent changes in vulnerability.

These subjective assumptions do not influence the main conclusion of our study, namely the need to analyse changes in flood risk by considering the whole range of drivers. This effort is still to be undertaken to fully understand the risk and to devise appropriate measures for risk reduction going beyond technical flood protection and focussing only on adverse consequences of climatic changes. Using the proposed blue print, the effect of different measures under more elaborated and specific assumptions can be explored at other sites, possibly accompanied by cost-benefit analyses.

2.6. Conclusions

In this study, a comprehensive sensitivity analysis was performed considering six different components related to hazard, exposure and vulnerability. The sensitivity analysis was combined with the "derived flood risk analysis based on continuous simulation (DFRA)" proposed by Falter et al. (2015). This framework was applied to the mesoscale Mulde catchment in Germany in order to explore the effects of plausible changes in flood risk chain components on risk estimates and to understand interactions among different components.

Our study finds that the largest contribution to flood risk changes comes from the change in river system considering heightening of river dikes. In this case, EAD (expected annual damage), aggregated at the catchment scale, is at most EUR 1.1 million. Interestingly, climate change impacts would be offset by these river system changes. However, dike rising might not be a feasible option because it is costly, requires space, and has long implementation times. Alternatively, changes in land use and vulnerability could be considered to reduce economic damage and were shown to be capable of compensating for adverse impacts of climatic changes. In terms of feasibility, vulnerability reduction is more realistic; decrease in settlement areas is a long-term approach and rarely implemented even in highly flood-prone areas, as additional factors other than the actual flood risk play a role in the decision to resettle an area. The effect of climatic changes on flood risk is modest in our setting. This is a consequence of climatic changes being out of phase with flood generation: large floods occur in summer when precipitation change is small. The majority of floods occur in winter where climatic change is substantial; however, these floods are typically small and do not cause large damage. Change in catchment system has a visible impact in the upstream reaches because most of the reservoirs are located there. Implementing storage capacity has a surprisingly modest effect on EAD. This results from the operational setting, as only floods higher than the 100-year event are influenced by the reservoirs, and the fact that EAD is typically dominated by the contribution of smaller floods.

Although the results are specific to the case study and depend to some extent on our choices in the implementation of this framework, some general conclusions can be derived.

The risk, quantified as EAD, varied by a factor of 40, from EUR 0.1 million to 4 million, across the range of change scenarios. This is a very high variation given the fact that our change scenarios represent possible changes that can occur within a few decades. This result points to the significant volatility that can be associated with flood risk. It underscores the necessity to monitor changes in risk regularly.

Our literature analysis revealed that past studies on changes in flood risk have almost exclusively focused on effects of climate change and land use change. Our analysis demonstrates that other components that have been neglected can be even more important. Hence, the study calls for more comprehensive analyses of changes in flood risk.

The effects of external drivers, i.e. drivers which cannot be controlled within the catchment (in our case climate change and increase in asset values), can be offset by internal factors. This points to the options of local stakeholders to counteract flood risk growth due to climate change and economic growth by flood risk management.

Almost all past studies on changes in flood risk have used EAD as a risk indicator. Since EAD is typically dominated by the contribution of small and medium floods, management options which reduce the damage for large floods are penalized by this limitation to EAD. A more comprehensive investigation, e.g. by considering effects across the risk curve, seems necessary.

Data availability

The data used in this paper are not publicly accessible; however, the authors can be contacted by email (duhametin@gmail.com, dung@gfz-potsdam.de, kai.schroeter@gfz-potsdam.de) for help in acquiring such data.

2.S. Supplementary for Chapter 2

Supplementary Table 2.1: Simulation-based studies on the causes of flood risk changes and their relative contributions.

Study	Time frame, region	Drivers considered							Risk indicators	Results
		Climate change (H)	Land subsidence (H)	Change in GDP (E)	Change in population (E)	Change in asset values (E)	Change in land use (E)	Change in cropland area(E)		
Alfieri et al. (2015)	1990-2080, Europe (28 countries)	✓		✓	✓				EAD, EAP	▪ Risk increases by an average of 220%, due to climate change only. ▪ When socio-economic development pathways are included, current mean estimates of EUR 5.3 billion of EAD increase to EUR 20-40 billion in 2050, EUR 30-100 billion in 2080 and current mean value of 216,000 EAP range between 500,000-640,000 in 2050, 540,000-950,000 in 2080.
Arnell and Gosling (2016)	2050, global (20 regions)	✓		✓	✓	✓		✓	EAD, EAP	▪ Climate change has the potential to considerably change human exposure to flood, but for different climate scenarios this impact is highly uncertain. ▪ The ranges of risk indicators for different climate models are substantially higher than the ranges for emission and socio-economic scenarios under a given climate model.
Bouwer et al. (2010)	2040, south Netherlands	✓				✓	✓		EAD, Loss probability curves	▪ Increase in expected damage due to change in asset values and land use is between 35-172 % while climate change causes 46-201 % increase in damage by 2040. ▪ For different land use categories, losses remain largely unchanged. ▪ Impact of change in assets are quite significant, they may double damage values.

Budiyono et al. (2016)	2030, Jakarta	✓	✓				✓	EAD	▪ As a result of combinations of all future scenarios, median increase of 180 % by 2030. ▪ Land subsidence as a single driver has the largest contribution which increases risk by 126%. ▪ No clear signal is found on the effect of climate change on the flood risk. Climate change results found highly uncertain. ▪ If land use changes with a same rate as the last 30 years, change in land use leads to large increase in the flood risk.
Elmer et al. (2012)	1990-2020, Mulde River, Germany	✓				✓	✓	EAD	▪ Climate change impact is important but not dominant. ▪ The expansion of residential areas (land use change) is the main driver of flood risk.
Feyen et al. (2009)	2071-2100, Europe	✓					✓	EAD	▪ Both climate change and land use change have significant effects on future flood risk increase. ▪ Increase in exposure due to urbanization outweighs effects of climate change.
Feyen et al. (2012)	2071-2100, Europe	✓						EAD, EAP	▪ Flood damages are anticipated to rise across Western Europe and to decrease across north-eastern parts of Europe. ▪ Current annual damage of EUR 6.4 billion and 250,000 people exposed are projected to EUR 14-21.5 billion annual damage and 400,000 people exposed by the end of the century due to climate change.
Hall et al. (2003)	2030-2100, England and Wales	✓		✓	✓	✓	✓	EAD, EAP	▪ Socio-economic drivers have more influence on increasing flood risk than by climate change. ▪ Scenario with combination of highest economic growth and increasing flood frequency can cause up to 20-fold increase in risk. ▪ Change in asset values has higher impact on flood risk. ▪ Scenario with great change in climate can double number of people at risk.
Hattermann et al. (2014)	2011-2100, Germany	✓						EAD	▪ Due to climate change, flood losses considerably increase. ▪ On average, total annual damage increases from EUR 465 million to EUR 993 million by the end of century.

Lung et al. (2013)	2011-2040 and 2041-2070, Europe	✓				✓	✓	3 impact indicators related to 100-year flood: percentage of flooded area; mean water depth of flooded area; percentage of commercial & industrial areas within flooded area (only for 2011-2040)	▪ To identify potential impacts of flood, combination scenarios of climatic and non-climatic drivers found to be crucial. ▪ Throughout Europe, there are slight increase in flood risk due to climate change mainly. ▪ The interactions between human settlements and hydro-geographical settings of the regions may increase flood risk. For example, catchments with major river systems have higher flood risk.
Muis et al. (2015)	2000-2030, Indonesia	✓					✓	EAD	▪ Climate change was found as highly uncertain on flood risk. ▪ Land use change (urban expansion) is the main driver of flood risk. ▪ This has been emphasized that increase in exposure will result in 76 % increase in flood risk, on average.
Rojas et al. (2013)	2000-2080, European Union	✓		✓	✓	✓		EAD, EAP	▪ Depending on the combined effect of climate change and socio-economic changes, there are significant increase in future damages and number of people affected by floods. ▪ By the combination of all drivers, number of people affected increases from 200,000 up to 360,000. ▪ The largest share of damages is due to change in asset values, GDP and population projections (socio-economic changes).
Te Linde et al. (2011)	2030, Rhine catchment	✓					✓	EAD	▪ Increase in EAD ranging from 54% to 230% in 2030 compared to 2000, depending on climate change and land-use scenarios. ▪ Approx. 75 % of increase attributed to climate change.

Chapter 3

The role of spatial dependence for large-scale flood risk estimation

Authors: Ayşe Duha Metin, Nguyen Viet Dung, Kai Schröter, Sergiy Vorogushyn, Björn Guse, Heidi Kreibich, Bruno Merz

Abstract

Flood risk assessments are typically based on scenarios which assume homogeneous return periods of flood peaks throughout the catchment. This assumption is unrealistic for real flood events and may bias risk estimates for specific return periods. We investigate how three assumptions about the spatial dependence affect risk estimates: (i) spatially homogeneous scenarios (complete dependence), (ii) spatially heterogeneous scenarios (modelled dependence) and (iii) spatially heterogeneous but uncorrelated scenarios (complete independence). To this end, the model chain RFM (regional flood model) is applied to the Elbe catchment in Germany, accounting for the spatio-temporal dynamics of all flood generation processes, from the rainfall through catchment and river system processes to damage mechanisms. Different assumptions about the spatial dependence do not influence the expected annual damage (EAD); however, they bias the risk curve, i.e. the cumulative distribution function of damage. The widespread assumption of complete dependence strongly overestimates flood damage of the order of 100% for return periods larger than approximately 200 years. On the other hand, for small and medium floods with return periods smaller than approximately 50 years, damage is underestimated. The overestimation aggravates when risk is estimated for larger areas. This study demonstrates the importance of representing the spatial dependence of flood peaks and damage for risk assessments.

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3.1. Introduction

Floods frequently occur as destructive events throughout the world. In the period 1995-2015, there were around 3100 flood events which affected 2.3 billion people worldwide with overall damages of USD 662 billion (CRED and UNISDR, 2015). It is commonly stated that flood risk has increased rapidly in the past and will continue to increase in future due to the combined effects of climate change and socio-economic development (e.g. Rojas et al., 2013). In order to mitigate the destructive impacts of floods, sound flood risk assessment and management are essential.

During the last decades, flood risk management has gained considerable attention and has shifted from a hazard-focused approach to the broader risk-based perspective covering both physical and societal processes (e.g. Merz et al., 2010b, 2014a; Bubeck et al., 2016; Thieken et al., 2016). For instance, the EU Flood Directive (EC, 2007) was adopted in October 2007 to launch a flood risk assessment and management framework in Europe considering all aspects of flood risk, including the impacts on society.

Conceptually, flood risk is defined as the probability of the adverse consequences within a specified time period. It depends on three components: hazard, exposure and vulnerability (IPCC, 2012; UNISDR, 2013). Following this definition, flood risk assessment starts with quantifying the hazard. By combining hazard and socio-economic information, such as land use and asset values, exposure is assessed. Vulnerability is included by adding information on how flood-affected objects would be damaged. Overall, flood risk assessment attempts to estimate the characteristics, e.g. inundation depth and flood extent, of a range of potential flood events, the exceedance probabilities of these events and their consequences (e.g. Winsemius et al., 2013; de Moel et al., 2015). The results of flood risk assessments are often presented in maps, which exist in many different forms depending on their purpose (Merz et al., 2007; de Moel et al., 2009). Flood hazard maps contain flood characteristics, e.g. inundation extent, water depth, for given return periods. Flood risk maps additionally consider the adverse consequences, e.g. economic damage and number of affected people.

Flood mapping is typically based on a number of spatially uniform (or homogeneous) scenarios with given return periods (e.g. Rhine Atlas; ICPR, 2015). The scenario with T-year return period is composed of all flooded areas within the study area, whereas each location shows the T-year flood. Hence, the T-year flood map is produced by piecing together or mosaicking estimates of the local T-year flood based on extreme value statistics at individual gauges, assuming complete dependence between different locations. Based on this assumption, Ward et al. (2013) and Winsemius et al. (2013, 2015) estimated flood hazard and risk at the global scale, assuming homogeneous return period scenarios within regions. At the European scale, flood hazard and risk were assessed based on spatially homogeneous scenarios by Feyen et al. (2012), Rojas et al. (2013), Alfieri et al. (2014) and Bubeck et al. (2019). At the national scale, Dumas et al. (2013) investigated future flood risk in France, and Hall et al. (2005) assessed current and future flood risk in England and Wales by assuming uniform return periods for all flooded areas. Similarly, te Linde et al. (2011) estimated current and future flood risk along the river Rhine. Real flood events are, however, spatially heterogeneous as the flood generation depends on a range of processes in the atmosphere, catchment and river network, which vary strongly in space (e.g. Nied et al., 2017; Vorogushyn et al., 2018). The analysis of historical floods shows that return periods of peak discharges are typically very heterogeneous for a given event (Lammersen et al., 2002; Uhlemann et al., 2010; Merz et al., 2014b; Schröter et al., 2015).

Some studies consider the spatial variability of return periods of floods. One approach applies multi-variate distribution functions to represent the dependence between flood peaks at multiple sites (e.g. Keef et al., 2009; Lamb et al., 2010; Ghizzoni et al., 2012; Thieken et al., 2015; Quinn et al., 2019). Based on a stochastic dependence model, spatially heterogeneous scenarios are generated and used for the risk assessment. This approach provides, however, only flood peaks, whereas the transformation of peaks into inundation areas requires event hydrographs. Hence, synthetic hydrographs are associated with the peaks, which is an additional source of uncertainties and errors (Grimaldi et al., 2013). These hydrographs are spatially inconsistent, i.e. not mass conservative, (though peaks are spatially consistent) and can be used for hydraulic calculations only for a limited river stretch. Another approach, proposed by Alfieri et al. (2015a, 2016a, 2017), combines inundation maps and resulting risk for heterogeneous return periods piecewise by interpolating between previously derived homogeneous return period maps. The spatially variable discharges are derived from a hydrological model driven by observations or climate models. This approach considers spatial dependence but still suffers from inconsistencies of inundation maps mosaicked piecewise. Further, an event-based simulation approach, where stochastic precipitation events are generated as input to a hydrological model, has been used (e.g. Rodda, 2001; Jankowfsky et al., 2016). The hydrological model simulates spatially dependent discharge hydrographs, which are then used by the hydrodynamic model to map inundated areas. A disadvantage of this approach is that the return period of discharge is assumed to be equal to the return period of precipitation, an assumption that does not necessarily hold. An alternative approach is a continuous hydrological-hydrodynamic simulation driven by long-term synthetic climate time series (e.g. Falter et al., 2015; Grimaldi et al., 2013). This approach is computationally expensive; however, it has a number of advantages, as discussed by Falter et al. (2015). Within the context of this paper, its most relevant advantage is that spatially consistent flood events can be modelled by considering the spatial dependence of the precipitation and of the flood generation processes in the catchment and river network.

According to our literature review, only a few studies consider spatial dependence when assessing flood risk. The large majority assume spatially homogeneous scenarios. This assumption is also the basis for flood hazard mapping, for instance, in Europe (de Moel et al., 2009), in Iowa in the US (Gilles et al., 2012), in Bangladesh (Tingsanchali and Karim, 2005) and in Honduras (Mastin, 2002). The assumption of complete dependence is appropriate for local risk estimates, but it may bias the risk estimates for larger areas. The purpose of our paper is to investigate this bias. To understand the effect of spatial dependency on risk estimates, we compare three assumptions of spatial dependence: (i) spatially dependent flood events with homogeneous return periods (complete dependence), (ii) spatially dependent events with heterogeneous return periods (modelled dependence), and (iii) spatially independent events with heterogeneous, i.e. randomly selected, return periods (complete independence). We explore the variation in the dependence effect with spatial scale and flood magnitude with respect to resulting flood damage.

To the best of our knowledge, our study is the first in-depth analysis of this bias at the scale of a large river basin. Lamb et al. (2010) and Wyncoll and Gouldby (2015) compared risk estimates for these three assumptions for smaller regions in the UK only (Leeds, York:

around 12 000 km^2; northeast England: around 15 000 km^2 in the former; Eden catchment: approximately 2400 km^2 in the latter); the effect of spatial dependence over large regions has not been studied. Further, they statistically generated spatially dependent peak flows and did not consider the spatial dependence of the flood generation processes, as it is possible with the continuous simulation approach of Falter et al. (2015). Jongman et al. (2014) assessed the effect of spatial dependence of flood peaks on flood damage in Europe but considered only modelled dependence versus full independence. They did not analyse the widespread assumption of homogeneous return periods.

To realistically represent the spatial dependence of the different flood processes, we use the derived flood risk analysis (DFRA) based on continuous spatially consistent modelling of the entire flood process chain (Falter et al., 2015). The model chain includes all processes from the precipitation through the catchment and river system to the damage mechanisms. The effect of spatial dependence is investigated for the Elbe catchment in Germany.

This paper is organized into six sections. Section 3.2 introduces the study area. Section 3.3 describes the model chain and how the risk estimates are obtained for the three dependence assumptions. Section 3.4 illustrates the risk estimation results under three spatial dependence assumptions. Further, we discuss these results in Section 3.5 and draw conclusions in Section 3.6.

3.2. Study Area: the Elbe catchment

The river Elbe is located in central Europe, with a length of 1094 km and total catchment area of 148 268 km^2. It can be subdivided into three parts: the upper Elbe, the middle Elbe and the lower Elbe. The upper Elbe mainly belongs to the Czech Republic and is dominated by mountains. In Germany, the upper Elbe reaches the northern German lowlands at Castle Hirschstein, followed by the middle Elbe reaching the weir Geesthacht. The lower Elbe starts downstream of Geesthacht and forms the Elbe estuary. Approximately two-thirds of the catchment belong to Germany, with the main tributaries Black Elster, Mulde, Saale and Havel (Fig. 3.1). In the present study, the analyses are presented for 29 sub-basins located within Germany. The complete Elbe catchment receives 628 mm precipitation per year, and the characteristic runoff regime is the rain-snow type (Nied et al., 2017).

Floods occur mainly in winter and spring, often as snowmelt or rain-on-snow floods. However, the largest floods tend to occur in summer. Heavy precipitation events associated with Vb cyclones have caused disastrous floods, such as the events in August 2002 and June 2013. The 2002 (EUR 8.9 billion damage) and 2013 flood events (EUR 5.2 billion) were the most severe flood events in the Elbe River basin in Germany for the last few decades (IKSE, 2015). Besides this, the river basin was affected by smaller floods in 2006, 2010 and 2011.

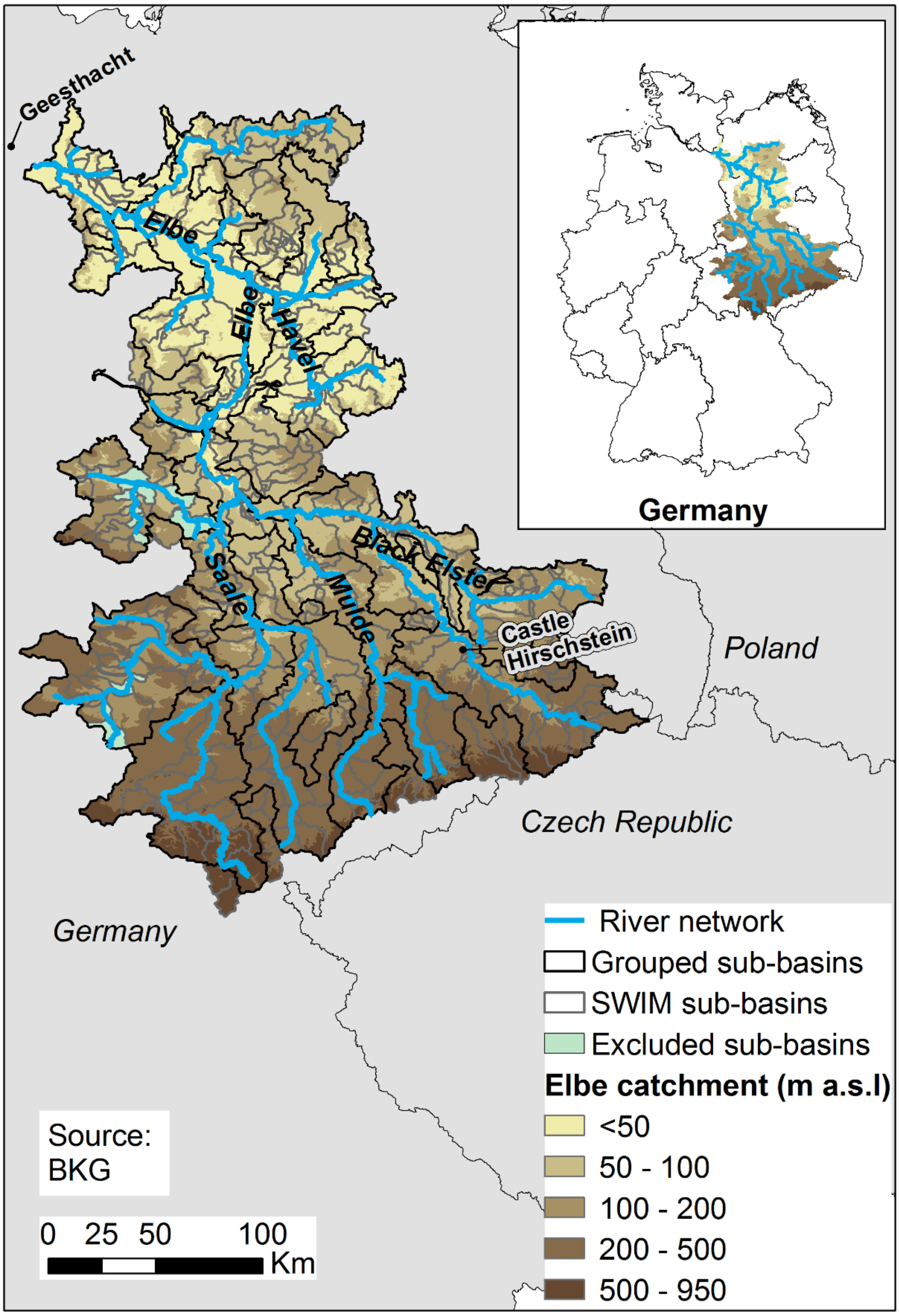

Figure 3.1: Study area in the Elbe catchment, including the main tributaries and sub-basins. The inset shows the location of the catchment within Germany. Data sources of figure: BKG (2012).

3.3. Methods

3.3.1. Regional flood model (RFM) for Germany

The regional flood model (RFM) has been developed for large-scale flood risk assessments, i.e. for areas of up to several 100 000 km^2. RFM is composed of a weather generator, rainfall-runoff model, 1-D channel routing model, 2-D hinterland inundation model and flood damage estimation model. The output from one model is used as input for the next model (Fig. 3.2). All processes along the entire flood risk chain are continuously simulated in a distributed manner. Consequently, spatially coherent precipitation patterns and flood preconditions of the catchment, including their influence on discharge peaks, water levels, inundation areas and damages, are considered.

In this study, RFM is run for time series of 10 000 years (100 realization of 100 years) on a daily time step. Synthetic meteorological time series at multiple sites are provided by a multi-variate weather generator. Further, continuous flood hydrographs at the sub-basin scale are calculated by a hydrological model, where antecedent catchment conditions are implicitly considered. The flow hydrographs are used as a boundary condition for the calculation of water levels in the river channels and inundation depths with a coupled 1D-2D hydrodynamic model considering levee overtopping. Finally, damage time series using a multi-variate flood loss estimation model for residential buildings are simulated. In this way, spatially consistent time series of flood damages at the SWIM sub-basin scale (196 sub-basins) are derived. The final risk results are represented at the grouped sub-basin scale (29 sub-basins). The model components are briefly described in the following. Details about RFM and calibration and validation results of the model components can be found in Falter et al. (2015, 2016) and Metin et al. (2018).

3.3.1.1. Regional Weather Generator RWG

The regional weather generator (RWG), proposed by Hundecha et al. (2009) and further developed by Hundecha and Merz (2012), generates synthetic weather at the regional scale. This multi-site, multi-variate auto-regressive model generates daily time series of meteorological variables, taking into account the spatial correlation structure. First, it generates daily precipitation series using the mixed gamma-Pareto distribution fitted to the observed data. Further, the model generates daily maximum, minimum, and mean temperature and solar radiation using Gaussian distributions conditioned on precipitation. RWG was set up for the area covering the entire Elbe, Rhine, Danube and Ems rivers using the observed climate data at 528 climate stations between the year 1951 and 2003 and was shown to capture daily precipitation extremes and seasonal precipitation patterns well (Hundecha et al., 2009).

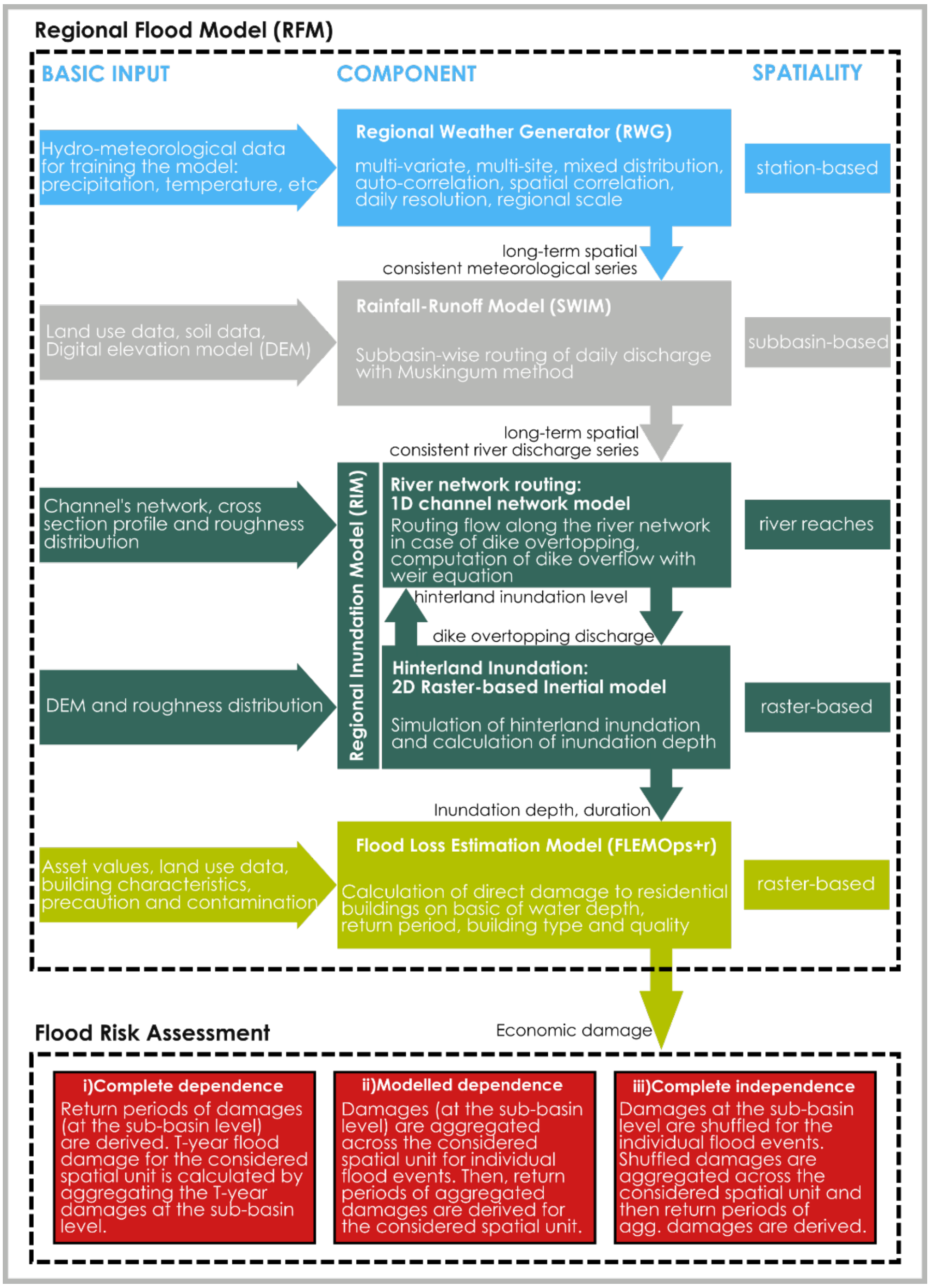

Figure 3.2: Workflow for the derived flood risk assessment (DFRA) with the Regional Flood Model (RFM).

3.3.1.2. Rainfall-Runoff Model SWIM

Discharge time series on a daily basis are derived with the semi-distributed hydrological model SWIM (Krysanova et al., 1998). The model has a three-level structure of spatial disaggregation: basins, sub-basins and hydrotopes. A hydrotope is a set of disengaged elementary units within the sub-basins, which are homogeneous in terms of land use and soil type. The hydrological processes, such as evapotranspiration, infiltration and snow melt, and different types of runoff are computed at the hydrotope level. The outputs from hydrotopes are integrated (area-weighted average) for each sub-basin. An average sub-basin area is in a range of 10 to 100 km^2. The runoff is routed by the Muskingum routing method between individual sub-basins and is aggregated at the basin scale.

The Elbe catchment was discretized into 2268 sub-basins in the watershed delineation of the SWIM model (SWIM sub-basins). A detailed soil map (BÜK 1000 N2.3, generated by the Bundesanstalt für Geowissenschaften und Rohstoffe, Hannover) and land use data (the CORINE land cover map) were used. The model was calibrated using observed daily climate data for the period 1981-1989. It was validated with observed discharge data on 20 gauging stations in the Elbe catchment for 1951-2003 (Falter et al., 2015; 2016; Metin et al., 2018). While discharge is simulated well in most parts of the Elbe catchment, peak flows are over- and underestimated in the range of ± 5% throughout most of the catchment (Falter et al., 2016). Discharge is mainly underestimated in Mulde and Black Elster and is overestimated in Saale. The model shows a poor performance for a few small SWIM sub-basins in the upstream part of the Saale catchment, likely due to not capturing reservoir effects. In addition, the poor performance at these mountainous sub-basins can occur due to the consideration of flood processes on a daily basis. In fact, the travel time of flood peaks can be smaller than 1 d at these sub-basins. Therefore, these areas are excluded in the present study (Fig. 3.1).

3.3.1.3. Regional Inundation Model RIM

The RIM simulates the water level along the river network and hinterland inundation depths. RIM consists of two-way coupled models: a 1-D hydrodynamic channel-routing model based on the diffusive wave equation and a raster-based 2-D hydrodynamic inundation model based on the inertia formulation (Metin et al., 2018). The overtopping flow is calculated by the 1-D model and is used as boundary condition for the 2-D model, which is back-coupled to the 1-D model. The overtopping is considered only at the main river network and higher-order tributaries that have a drainage area of 600 km^2 or more. This river network is explicitly modelled with the 1-D diffusive wave hydrodynamic model. The flood routing in smaller tributaries with drainage area below the above-mentioned threshold is done by the Muskingum routing within the SWIM model. The river geometry is described by simplified cross sections which include the overbank river geometry and dike crest elevation derived from the 10 m DEM provided by the Federal Agency for Cartography and Geodesy in Germany (BKG). Whenever the water level overtops the dike crest elevation, the overtopping flow is computed using the broad-crested weir equation.

The river profiles were manually extracted perpendicular to the flow direction every 500 m. Due to the low resolution of the 10 m DEM in relation to the dike geometry, the derived dike heights tend to be lower than in reality. Hence, a minimum dike height of 1.8 m was used for the river Elbe. The constant Manning's roughness of 0.03 $m^{-1/3}s$ was assumed in the river network. For the 2-D raster-based model, the 10 m DEM was resampled to 100 m computational grid found to represent the inundation characteristics with suitable computation time well (Falter et al., 2013).

The 1-D hydrodynamic channel-routing model was validated with observed data for 1951–2003 at eight gauging stations in the Elbe catchment (Falter et al., 2015; 2016). The performance of the 1-D model is acceptable even though there is a tendency to underestimate observed peak flows exceeding the bankfull depth. The simulated inundation areas were compared to the extreme flood in August 2002, the only event for which inundation depth and extent are available. Although the model tends to underestimate inundation extents, since it neglects dike breaches, it provides plausible inundation patterns.

3.3.1.4. Flood Loss Estimation Model FLEMOps+r

The direct economic damage to residential buildings is estimated by the Flood Loss Estimation Model for the private sector (FLEMOps+r). The model considers five inundation depth classes, two building quality classes (high quality or medium-low quality), three building types (single-family, semi-detached and detached, or multi-family houses) and three return period classes to estimate damage (Elmer et al., 2012). The model provides the damage ratio which is multiplied with the asset values of the inundated residential buildings to obtain the monetary damage.

Besides inundation depths and return periods, the model requires spatially detailed information on building qualities, building types and asset values. The mean building quality and cluster of building type composition was estimated on the municipal level on basis of INFAS Geodaten GmbH (2009). The asset values were determined considering the standard construction costs (BMVBW, 2005) and were spatially disaggregated using the digital basic landscape model ATKIS Basis DLM (BKG GEODATENZENTRUM, 2009). Municipal asset data were disaggregated by means of a dasymetric mapping approach (Wünsch et al., 2009). The damage was estimated according to output from the hydrodynamic model on a raster level by calculating the damage ratio according to the inundation depth and return period in the corresponding cell and the underlying information for building types and qualities per municipality (Thieken et al., 2008).

The model was validated on the micro- and meso-scale on basis of empirical damage data of the August 2002 flood in the state of Saxony in Germany (Elmer et al., 2010; Falter et al., 2015).

3.3.2. Flood Risk Assessment for Different Dependence Assumptions

We compute flood risk for three spatial dependence assumptions (Fig. 3.3): (1) complete dependence or homogeneous return periods across the river basin, (2) modelled dependence or heterogeneous return periods, and (3) complete independence, where flood peaks and associated return periods are randomly sampled. In scenarios (1) and (3) the discharges, inundation areas and damages are spatially inconsistent; i.e. they are mosaicked from the continuous simulations by selecting events and damages for corresponding return periods. The spatial variation in damages within the catchment depends on the spatio-temporal patterns of meteorological, hydrological and hydraulic processes. For instance, the flood damage downstream of the confluence of two tributaries depends on the superposition of the flood waves from these tributaries. The damage results of the modelled dependence should lie between the results of the two other assumptions, as they span the whole range from complete dependence to complete independence. Further, the modelled dependence results should be similar to those of the complete dependence for small areas and should move towards complete independence as the spatial scale becomes large.

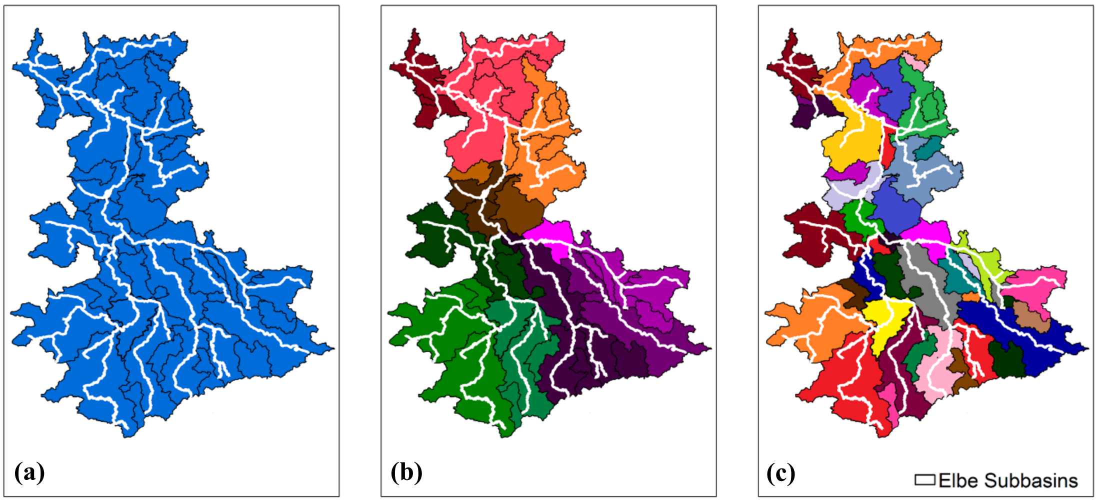

Figure 3.3: Conceptual representation of the three assumptions on spatial dependence: (a) complete dependence; (b) modelled dependence; and (c) complete independence. Return periods of damage are color-coded at the sub-basin level.

We characterize flood risk by the probability of damage (risk curve) and by the expected annual damage (EAD) computed as the integral of the risk curve. Damage values are calculated at the 100 m grid resolution for individual inundation events of the 10 000-year continuous flood simulation with RFM. An event requires that flood defences are overtopped at least at one location and that it affects residential assets, i.e. a non-zero damage occurs. If anywhere in the entire catchment overtopping occurs after at least 10 d of non-overtopping, this is defined as the start of a new event. Empirical return periods for damages aggregated for specific spatial units (e.g. sub-catchments) are determined using Weibull plotting positions. Damage at the level of the sub-basins (SWIM sub-basins) is then aggregated to larger spatial units (e.g. aggregation of sub-basins or the entire catchment) for individual flood events. These pairs, i.e. damage and associated return period, are used to construct risk curves and to calculate the EAD (Falter et al., 2015).

Under the assumption of complete dependence, all sub-basins within the considered spatial unit, e.g. the entire river basin, are assumed to experience a T-year flood damage at the same time. Hence, the T-year flood damage is calculated by aggregating the T-year damage values of all sub-basins estimated from individual (not necessarily concurrent) events. In the following, we refer to a T-year flood event as an event resulting in the T-year damage. This definition of a T-year flood event is different when compared to the traditional way based on the peak return period.

Under the modelled dependence assumption, damages are aggregated for individual flood events across the considered spatial unit, and return periods of aggregated damages are derived directly for this spatial unit. This approach aims to represent the true spatial and temporal dependencies of real-world flood situations. For example, for a T-year flood loss over the entire catchment, the return periods of damages in individual sub-basins are expected to be different from sub-basin to sub-basin. Furthermore, these return periods are expected to show a certain spatial pattern dictated by the spatial correlation of the flood generation processes.

Under the assumption of complete independence, the spatial correlations between damages of different sub-basins are destroyed. Damages of individual flood events are shuffled at the SWIM sub-basin level and aggregated for the considered spatial units. Return periods of these aggregated damages are determined for the spatial unit considered. As the aggregated damage and the risk curve depend on the specific realization of the shuffling, this procedure is repeated 1000 times. From this sample, the median is used to construct the risk curve, and additionally the 95 % confidence range is computed.

The risk curves and EAD are derived at the grouped sub-basin level (29 sub-basins in total, see Fig.3.1), as a higher resolution would lead to many instances where the number of damaging floods would be too low to construct meaningful empirical risk curves.

3.4. Results

3.4.1. Damage Estimations under three Dependence Assumptions for the Entire Catchment

The aggregated economic damages to residential buildings for the Elbe catchment and their corresponding return periods are illustrated in Fig. 3.4 for the three dependence assumptions. While the economic damage of the 1000-year event is estimated at around EUR 620 million under the assumption of complete dependence, it is around EUR 360 million for the modelled dependence scenario (70 % overestimation under the assumption of complete dependence). A strong overestimation is also given for smaller return periods down to approximately 150 years. Moreover, the assumption of complete independence may underestimate damage by 50 %. The extreme assumption of complete independence represents the lower limit for large return periods. For smaller return periods, however, we see the opposite effect. The damage is underestimated under the assumption of complete dependence for events with return periods smaller than 87 years.

The point where the risk curves of modelled dependence and complete dependence intersect is called the “intersection point” in the following. For return periods up to this intersection point, the complete dependence assumption underestimates the damage compared to modelled dependence; all sub-basins show either no or small damages, as the flood peaks are mostly below the flood defences. However, for the assumption of modelled dependence, the return periods vary, and a small to medium return period event at the scale of the entire Elbe catchment may be composed of many sub-basins without any damage but a few sub-basins with large damage because in these sub-basins the flood defences are overtopped. A similar explanation holds for the situation beyond the intersection point: the complete dependence assumption leads to events where all sub-basins tend to show large damages, as flood defences are overtopped everywhere. In contrast, under the modelled dependence assumption many sub-basins show large damages as defences are overtopped; however, there are also sub-basins without damage as a consequence of spatial variability.

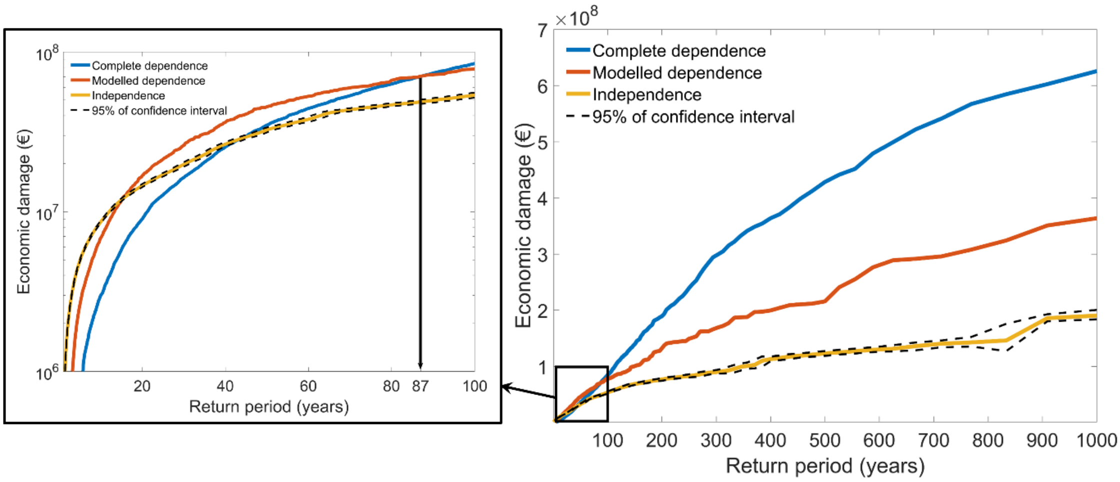

Figure 3.4: Risk curves for the Elbe catchment for three dependence assumptions (complete dependence, complete independence and modelled dependence). The left panel zooms in the risk curves up to the 100-year return period of damage.

The underestimation (overestimation) for small (large) return periods under the complete dependence assumption is a consequence of the strong link between the damages of the different sub-basins. For better understanding, Fig. 3.5 illustrates the spatial distribution of damages at the sub-basin level for the three dependence assumptions that lead to the 20- and 200-year event at the catchment scale. For the 20-year event, under the complete dependence assumption, all sub-basins show either no damage or small to medium damage, leading to comparatively small damage at the scale of the entire basin (Fig. 3.5a). The 20-year event for the modelled dependence assumption consists mainly of sub-basins without any damage, but due to dike overtopping single sub-basins may experience large damage. These sub-basins are clustered, in this case in the northwest of the Elbe catchment, illustrating the effect of spatial dependence. In contrast, the damages are not clustered under the complete dependence and independence assumptions. For the 200-year event (Fig. 3.5b), almost all sub-basins indicate large damage under the complete dependence assumptions, resulting in the overestimation under complete dependence assumption for the entire catchment.

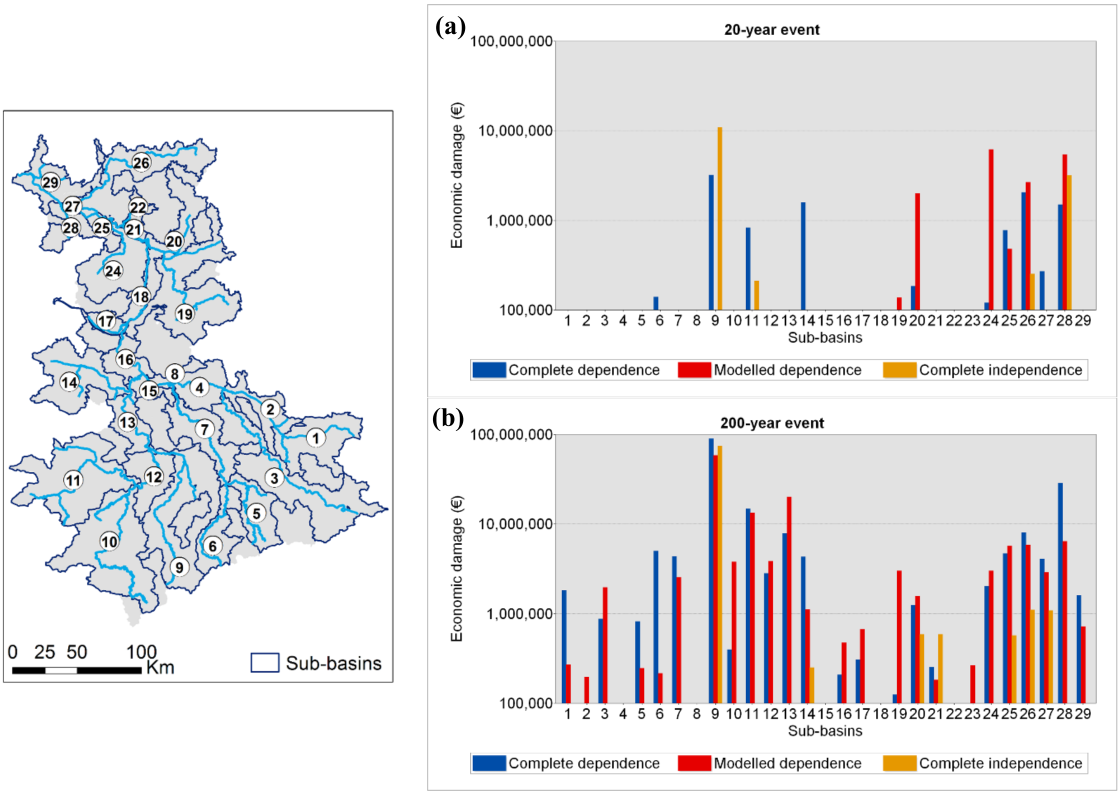

Figure 3.5: Distribution of damages at the sub-basin level for (a) the 20-year event and (b) 200-year event for three dependence assumptions.

3.4.2. Variation in damage estimations with spatial scale under three dependence assumptions

To understand how the risk estimates for the three dependence assumptions vary with spatial scale, the risk curves for aggregations of sub-basins from upstream to the entire catchment are given in Fig. 3.6. As a general rule, smaller regions should be characterized by stronger spatial dependence of damage. This should lead to (1) an increasing difference between the risk curves of the three dependence assumptions with increasing scale and (2) a shift of the modelled dependence risk curve from the complete dependence towards independence with increasing scale. Both effects are seen in Fig. 3.6.

The intersection point shifts from return periods of a few hundred years for smaller aggregation areas, i.e. sub-basins 1 to 8 (up to 11 800 km^2; upper panels in Fig. 3.6), to approximately 90 years for the larger areas. The intersection point is mainly affected by the threshold where damage occurs, i.e. by the flood protection or elevated banks. This strong shift in the intersection point is, however, not a consequence of very different flood defence standards in the up- and downstream parts of the Elbe catchment but rather results from data and modelling errors. In particular, the small-scale variability in precipitation extremes appeared to be insufficiently well captured by the weather generator in some sub-basins due to varying station density used for parameterization. Sub-basins 1 to 8 (Mulde and Black Elster rivers) experience very small damage even for high return periods, while the opposite is true for sub-basins 9 to 14 (Saale River). This is explained by the underestimation of damage for the Mulde and Black Elster rivers and overestimation for the Saale River.

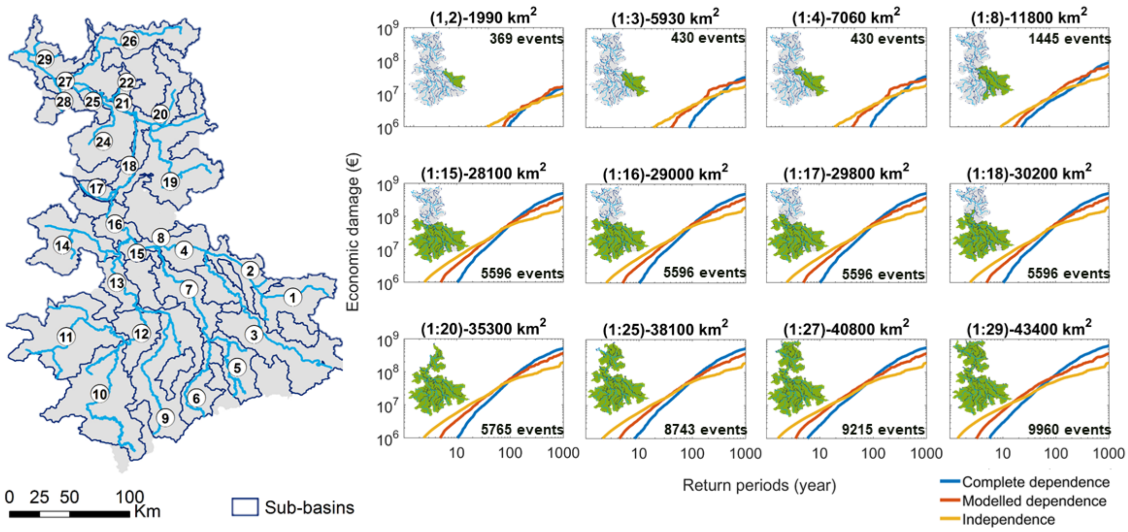

Figure 3.6: Sub-basins in the Elbe catchment (left) and risk curves of aggregations of sub-basins (right) under complete dependence, modelled dependence and independence. The aggregated sub-basins are ordered along increasing scale and are denoted by the green colour within each risk curve and the colon (:) between start and end sub-basin numbers.

3.4.3. Errors in expected annual damage (EAD) and in 200-year damage under 'false' assumptions of spatial dependence

Besides the risk curve, the EAD and the damage for a T-year return period are important risk measures. We assess here the 200-year return period damage, which is particularly important for the insurance sector. Their percentage error under the complete dependence and independence assumptions, compared to the modelled dependence assumption, is given in Fig. 3.7 for the entire Elbe catchment. The false assumptions about spatial dependence do not impact the EAD estimation. The EAD is the sum of 29 random variables, i.e. the damages for the 29 sub-basins. As the mean value of a sum of random variables is not influenced by the correlation between the variables, the spatial correlation can be neglected when one is only interested in EAD. However, correlation influences the variance of a sum of random variables. Hence, for other values, such as the 200-year event, it is crucial to include the 'true' spatial dependence pattern. In our case, the damage for the 200-year event is overestimated (underestimated) under complete dependence (independence) by around 40 %.

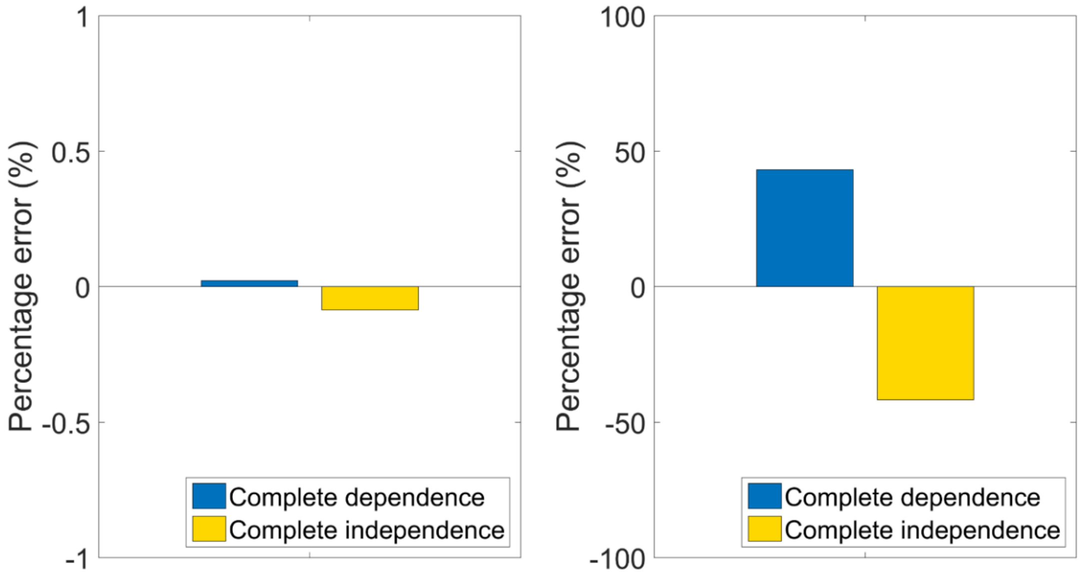

Figure 3.7: Percentage error in expected annual damage (EAD) (left) and in economic damage for the 200-year event (right) under the assumptions of complete dependence and complete independence for the entire Elbe catchment.

3.5. Discussion

This study investigates the effects of spatial dependence of flood generation processes on risk estimates. It compares the "true" dependence scenario to the two endpoints, i.e. complete dependence and complete independence. It is shown that the assumption of complete spatial dependence, which is often used in risk assessments, leads to under- and over-estimation of flood risk for small and large return periods, respectively.

Although several papers have suspected that the complete dependence assumption may bias risk estimates, this bias has been investigated by the two studies of Lamb et al. (2010) and Wyncoll and Gouldby (2015) only. As these studies are limited to small and medium study areas up to 15 000 km^2, our study is the first investigation for a large-scale river basin. In addition, our study uses a more elaborate setup, as the spatial dependence of all processes along the flood risk chain, from the precipitation to the damage, is included. The larger study area allows us to investigate how the differences in risk estimates change with increasing scale. The modelled dependence estimate tends to be similar to the complete dependence scenario for smaller areas and to shift towards the independence scenario when the scale is increased. However, this shift is not very prominent. We assume that the variety of processes that are involved in the generation of damage blurs a clear signal when going from smaller to larger scales. The spatio-temporal dynamics of flood damage events is influenced not only by the spatio-temporal dynamics of the triggering rainfall event and antecedent catchment conditions but also by the topology of the river network, flood wave superposition, structural flood defences, and the spatial distribution of the asset values and their vulnerability. More work is needed to better understand how the spatial dependencies of different processes along the risk process chain influence the mismatch between modelled and complete dependence. If simple rules can be derived, they could be used to decide whether the spatial dependence of the damage-generating processes needs to be taken into account or whether a simplified analysis neglecting spatial dependence would suffice.

We are not aware of any study which discussed the intersection point between modelled and complete dependence. We show that the overestimation of risk by the complete dependence assumption that has been reported by Lamb et al. (2010) and Wyncoll and Gouldby (2015) applies to large return periods only. For small return periods the complete dependence assumption underestimates risk. This behaviour, and the location of the intersection point, is mainly affected by the damage threshold controlled by the flood defence level or elevated banks.

Although each model in RFM has some limitations, RFM represents well the spatial patterns of the different flood generation processes (Falter et al., 2016, Metin et al., 2018). For this study, the model limitations of hydrologic, hydraulic and damage model accuracy are not seen as major concerns because the different assumptions on spatial dependence are investigated by using the same model chain. The spatial performance of the weather generator with regards to precipitation, however, can have an effect on the final results. It is also more challenging for the weather generator than capturing the local statistics as previously discussed in the literature (e.g. Serinaldi and Kilsby, 2014). The spatial dependence of high precipitation is often overestimated due to the use of isotropic covariance function (Serinaldi and Kilsby, 2014) as also applied in our case. Although this limitation would presumably translate into the higher dependence of discharge peaks, we believe, this is not critical for the presented study. The results of modelled dependence are located between complete dependence and complete independence for high return periods. With an ideal weather generator, they would be closer to the complete independence. Thus, our estimates for the difference between the assumption of complete dependence and modelled dependence can be regarded as conservative. Hence, the major conclusion challenging the assumption of homogeneous return periods (complete dependence) still holds. Another limitation is the assumption that dikes can only be overtopped but do not breach. In reality, dike breaches may lead to significant reductions of flood peaks downstream of breach locations, and larger outflow volumes can be observed in the inundated area compared to the no-breach case. However, the modelling of dike breaching requires high computational time because the prediction of breach locations is difficult, and hence a stochastic approach including multiple Monte Carlo runs would be needed. In this study, the consideration of dike breaching would increase the computational time, which is already high. Hence, the number of inundation events and damages may be underestimated. This could affect the intersection point, i.e. the point where the underestimation of the complete dependence turns into overestimation. Including dike breaches in the model might shift the intersection point to smaller return periods.

As expected from statistical reasoning, our study confirms that the EAD is not biased by false assumptions on spatial dependence. If one is only interested in the EAD, spatial dependence can be neglected, which drastically simplifies the analysis. However, EAD is a rather limited indicator of risk, as discussed, for instance, by Merz et al. (2009). Further, specific purposes demand assessments of certain risk scenarios for which spatial dependence is crucial. According to Article 101 of the European Solvency II Directive, insurance companies are required to prove that they can cover at least damage events with a return period of 200 years (EC, 2009). The spatial dependence in damage is also highly relevant for disaster management or large-scale, strategic flood planning. It is important, for instance, to understand the disaster management resources that are needed for large-scale floods.

3.6. Conclusions

This paper analysed the impact of spatial dependence in flood damage generation on risk estimates for the large-scale Elbe River basin in Germany. The "true" spatial dependence was simulated with the continuous flood risk modelling approach proposed by Falter et al. (2015), where all processes, including their spatial dependence, from the flood triggering rainfall to the damage processes, are considered. The bias between the widespread but false assumption of complete dependence and the modelled dependence was investigated as a function of spatial scale.

Our results show that for extreme events the economic damage can be strongly overestimated when homogeneous return periods are assumed across the catchment. For the Elbe river basin, damage is overestimated by about 40 % for the 200-year event and by almost 100 % for the 500-year event. On the other hand, for events with small to medium return periods, the complete dependence assumption underestimates damage. The intersection point where the underestimation turns into an overestimation depends mainly on the damage threshold, i.e. on the flood defence level in protected areas.

The spatial scale, for which a risk estimate is sought, decides whether the modelled dependence assumption is closer to complete dependence or independence, respectively. The modelled dependence risk curve is closer to complete dependence for the upstream areas comprising the Mulde and Black Elster rivers; with increasing scale it shifts towards the independent case. Consequently, the overestimation under the complete dependence assumption increases with larger areas. As a general rule, the true dependence might be approximated by the complete dependence assumption for smaller regions, whereas for larger regions the independence assumption might serve as an approximation in a rough analysis when including the spatial dependence seems too costly or demanding. However, our study does not allow specifying in a generic way the scales at which a certain assumption might serve as approximation. More systematic analyses are necessary to answer this question.

If one is only interested in the expected annual damage (EAD), then false assumptions on spatial dependence do not bias its estimate. Although the EAD is an important risk indicator, for example for cost-benefit analyses of flood mitigation or in the insurance sector, we strongly advocate considering the complete risk curve, as it gives a much richer perspective on the risk and the effects of mitigation measures. Hence, we conclude that it is of highest relevance to realistically represent the spatial dependence of flood damage for large-scale risk estimates.

Data availability

The data used in this paper are not publicly accessible; however, the authors can be contacted by email (duhametin@gmail.com, dung@gfz-potsdam.de, kai.schroeter@gfz-potsdam.de) for help in acquiring such data.

Chapter 4

Biases in national and continental flood risk assessments by ignoring spatial dependence

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Abstract

Recently, flood risk assessments have been extended to national and continental scales. Most of these assessments assume homogeneous scenarios, i.e. the regional risk estimate is obtained by summing up the local estimates, whereas each local damage value has the same probability of exceedance. This homogeneity assumption ignores the spatial variability in the flood generation processes. Here, we develop a multi-site, extreme value statistical model for 379 catchments across Europe, generate synthetic flood time series which consider the spatial correlation between flood peaks in all catchments, and compute corresponding economic damages. We find that the homogeneity assumption overestimates the 200-year flood damage, a benchmark indicator for the insurance industry, by 139 %, 188 % and 246 % for the United Kingdom (UK), Germany and Europe, respectively. Our study demonstrates the importance of considering the spatial dependence patterns, particularly of extremes, in large-scale risk assessments.

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4.1. Introduction

Flooding is a major hazard, with global average annual flood loss estimated to USD 104 billion (UNISDR, 2015). Flood damages have been increasing in the last decades (Winsemius et al., 2015) and are projected to increase further, mainly due to a combination of climate change and socio-economic development (e.g. expansion of urban areas and economic growth in flood hazard zones) (Alfieri et al., 2017; Dottori et al., 2018). In Europe, observed data suggest that climate change has already significantly altered flood magnitude, timing and extent. Blöschl et al. (2019) demonstrate clear regional patterns of both increase and decrease in observed river flood discharges in the past few decades. Blöschl et al. (2017) additionally, finds the changing climate shifts timing of European floods. Furthermore, Kemter et al. (2020) highlight the trends in flood extent, i.e. the area simultaneously experiencing peak flows at multiple gauges. They demonstrate the alignment of trends in magnitude and extent. Disaster risk reduction requires to assess flood risk, defined as the relation between the likelihood of flood events and their potential adverse consequences (IPCC, 2012; UNISDR, 2013; Kreibich et al., 2017). In the last decade, flood risk assessments have been extended to the national and continental scale (e.g. Feyen et al., 2012; Ward et al., 2013; Rojas et al., 2013; Winsemius et al., 2015). These large-scale assessments have often assumed spatially homogeneous flood scenarios, where each area within the large-scale region is subject to an event with the same exceedance probability or return period (Metin et al., 2020). For instance, Ward et al. (2013) and Winsemius et al. (2015) at the global scale and Feyen et al. (2012), Rojas et al. (2013) and Bubeck et al. (2019) at the European scale, and Te Linde et al. (2011) at the scale of the Rhine basin estimate flood risk in terms of expected annual damage (EAD) and/or expected annual affected population (EAP) under the assumption of homogeneous return periods. Other studies quantify risk in terms of damage or affected population for specific return period floods. Hirabayashi et al. (2013) provide the number of people exposed to 100-year flood assuming homogeneous scenarios at the global scale. For the USA, Wing et al. (2018) estimate damages and number of people exposed to present and future 50-, 100- and 500-year floods. Hall et al. (2005) and Dumas et al. (2013) quantify economic damage and/or number of people exposed to the 100-year flood apart from EAD for England and Wales and for France, respectively. Furthermore, Winsemius et al. (2013) assess economic damages for the 15- and 30-year floods in Bangladesh.

In contrast to the homogeneity assumption, floods show substantial spatial variability in the associated atmospheric, catchment and river network processes, and as a consequence, the return periods of discharge peaks vary considerably along the river, across the catchment and across larger regions (e.g. Schröter et al. 2015). This interplay of different processes in the generation of floods leads to distinct flood regimes, i.e. flood timing and magnitude, and spatially heterogeneous dependence patterns in flood peaks (Nied et al., 2017; Merz et al., 2018; Vorogushyn et al., 2018). Therefore, the assumption of homogeneous return periods is an unrealistic representation of the flood behaviour (Lamb et al., 2010; Metin et al., 2020). This may not be a problem for smaller areas where flood peaks at different locations may be highly correlated. However, at the national or continental scale, the homogeneity assumption may bias regional risk estimates. Given the recent rapid developments in large-scale floods risk assessments and the widespread use of the homogeneity assumption, it is an urgent question whether this assumption introduces significant biases.

There are very few studies which have discussed the effect of spatial dependence on flood risk estimates. Lamb et al. (2010), Wyncoll and Gouldby (2015) and Metin et al. (2020) compare three spatial dependence assumptions: (1) complete dependence, i.e. spatially homogeneous flood scenarios, (2) modelled dependence, i.e. spatially dependent scenarios, attempting to represent the real-world spatial dependence, and (3) complete independence, i.e. flood magnitudes vary randomly in space. These studies suggest that the often-used complete dependence assumption overestimates flood damages for large return periods and underestimate damages for small return periods, whereas the EAD values are marginally affected by spatial dependence according to Metin et al. (2020). However, these studies are limited in scale, as Lamb et al. (2010) and Wyncoll and Gouldby (2015) investigate small regions in England (up to 15 000 km^2) and Metin et al. (2020) analyze the Elbe catchment in Germany (around 150 000 km^2). Further, Alfieri et al. (2016b) and Jongman et al. (2014) compare risk estimates for the modelled dependence and complete independence assumptions for several European countries and for Europe, respectively. However, they do not explore the widespread assumption of complete dependence. Regional flood risk estimates may also be affected by tail dependence between flood peaks at different locations. If tail dependence exists, for instance, weak correlation between mean values of the random variables but strong correlation between extremes, it needs to be incorporated in multivariate risk assessments (Ganguli and Merz, 2019). However, the effects of tail dependence have not been sufficiently investigated for regional flood risk assessments.

Here, we develop a multivariate, copula-based statistical model to generate 10 000 years of spatially dependent time series of AMS (Annual Maximum Streamflow) at 379 stations across Europe ("Methods"). These synthetic time series are transferred into inundation areas and economic damages, using the simulation results of Alfieri et al. (2015a). Regional risk curves, relating the damage within a given region to its probability of exceedance or return period, are then derived for the three spatial dependence assumptions, i.e. complete dependence, modelled dependence and complete independence. Risk estimates are given for three regions, Europe, Germany and the UK. The latter two are selected due to the high density of discharge stations in these areas. To investigate the effect of tail dependence, we use three copula models with different degree of tail dependence.

4.2. Methods

4.2.1. Multivariate dependence model

We adopt a copula-based multivariate model to represent the spatial dependence structure of annual maximum streamflow (AMS) of daily discharge at multiple locations over Europe. The copula approach is based on Sklar's theorem (Sklar, 1959), which sets up a link between a joint distribution and its marginal distribution functions. One key advantage of the approach is that it can separate the dependence structure from the marginal distributions (Joe, 1997; Genest and Favre, 2007). Among the different classes of copulas, elliptical copulas offer convenience in model construction and computation of high dimensional problems and have close relation to the classical multivariate method (Renard and Lang, 2007; Okhrin et al., 2017). We apply the Gaussian and Student-t copulas which are the most widely used elliptical copulas. Both are symmetrical copulas. The Gaussian copula is completely determined by the correlation matrix as its mere parameter which is relatively simple to estimate. However, it lacks tail dependence which measures the co-movement in the tail parts of the distribution. To overcome this shortcoming, the Student-t copula can be seen as an extension of the Gaussian copula as it retains the use of correlation structure and introduces an additional parameter, the degree of freedom (*df*) which supports the co-movement in extreme behaviour. The Student-t copula therefore has tail dependence. The tail dependence of the Student-t copula gets weaker with a higher *df*. In the limiting case where *df* approaches infinity, Student-t copula becomes Gaussian copula.

In this study, the correlation matrix of the Gaussian copula is estimated by the method of moments based on Kendall's tau. For the Student-t copula, we use the method of Mashal and Zeevi (Mashal and Zeevi, 2002), which combines the method of moments based on Kendall's tau for estimating the correlation matrix and the maximum pseudo-likelihood-like estimation for determining the number of degrees of freedom. Particularly for a large number of variables, as in our case, the correlation matrix can be estimated incorrectly (not positive definite) due to the truncation error and/or missing data. Therefore, we correct the correlation matrix by the algorithm nearPD (nearest positive definite matrix (Higham, 2002)) available in the package Matrix of the R programming language.

For marginal distributions, we fit the Gumbel distribution to 379 AMS time series using the maximum likelihood method (Coles, 2001) then test the goodness-of-fit using Anderson-Darling (AD) test (Marsaglia and Marsaglia, 2004) and Cramer-von Mises (CvM) test (Csörgő and Faraway, 1996). Gumbel distribution is preferred due to its simple structure. At 372 stations the fitting passes the tests. We then fit the Generalized Extreme Value (GEV) distribution to data at the remaining 7 stations. Supplementary Fig.4.1 shows that all testing p-values are larger than the significance level of 0.05 (with median p-value of 0.81 for the CvM test and 0.84 for the AD test) indicating good fitting at all stations.

4.2.2. Discharge data and simulation of AMS at multiple locations

Based on daily discharge data with at least 50 years of continuous data from the Global Runoff Data Centre (GRDC, 2020), we derive AMS time series for a common, 31-year time period (1968-1999). We consider 379 gauging stations in 21 European countries (Fig. 4.1a). The station geo-location is matched to the 5-km gridded river network of the European Flood Awareness System (EFAS, see Thielen et al. (2009)), using criteria based on proximity, naming, and a maximum error between modelled and official upstream area of 20%. In addition, stations with upstream area smaller than 500 km^2 are excluded, so that discharge peaks can be linked to the corresponding inundated area at 100 m resolution for different return periods (Alfieri et al., 2014, 2015a). The area threshold of 500 km^2 is the minimum upstream area simulated in the considered JRC European inundation maps, which we use for damage estimation. The copula-based model is used to generate 10 000 years (100 realizations x 100 years) of AMS at the 379 stations.

4.2.3. Damage calculation from AMS series

The 10 000-year synthetic AMS are used to calculate flood damage. In a first step, AMS values are associated with the maps of flood depth and extent at 100 m resolution. For this, the relation between discharge peaks and return periods are estimated by the Gumbel distribution using the L-moments approach for parameter estimation (Hosking, 1990). Only discharge peaks exceeding the 2-year return period, which is a good proxy for bankfull discharge (Carpenter et al., 1999), are taken into account for damage estimation. The linkage between discharge peaks and inundation depths is obtained from previous 2D hydraulic simulations with the LISFLOOD-FP model (Alfieri et al., 2015a). The maximum water depths for selected flood return periods are computed using synthetic flood hydrographs consistent with the flow duration curve at each 5 km river section along the European river network. Flood depth and flood extent at 100 m resolution are estimated on the basis of the CCM Digital Elevation Model (Vogt et al., 2007). Roughness coefficients for the LISFLOOD-FP model are linked to the 100 m resolution land use map of Europe Batista e Silva et al. (2013).

In a second step, direct economic damage for all economic sectors (i.e. residential, commerce, industry, transport, infrastructure, agriculture) is estimated using the flood maps and country-specific depth-damage functions, given by Huizinga (2007) for different land use classes. Regional differences in asset values for a given land use class are considered by rescaling the depth-damage functions with the GDP (Gross Domestic Product) Purchasing Power Standards of 2007. The damage for selected return periods (T = 10, 20, 50, 100, 200, 500 years) is assessed at 100 m resolution and then aggregated to 5 km resolution through the method of Areas of Influence (AoI), described in Alfieri et al. (2015a). Flood damage is calculated upstream of each river station for two scenarios, i.e. with and without flood protection. For the scenarios with flood protection, the damage is set to zero if the return period of the discharge peak is smaller than the flood protection level for the corresponding river section. For details on the economic impact assessment (see Alfieri et al. (2015a; 2016b)). Finally, we calculate economic damages on the European scale over 10 000 years by interpolating and extrapolating for AMS values with return periods larger than 500 years. Our damage estimates do not consider the complete European area (1) as the flood maps cover only river catchments larger than 500 km^2, (2) as the impact model cannot be run due to data limitations in some parts of Europe, e.g. in Iceland, Switzerland, Russia and a few countries in the Balkans, and (3) as significant parts of Europe are not covered by observational gauge data in GRDC database. Hence, our damage estimates cover part of the three regions the UK, Germany and Europe which are selected for the presentation of the results.

4.2.4. Flood risk assessment for different spatial dependence assumptions

We compute direct flood damages and risk curves for three regions (the UK, Germany, Europe) and for three spatial dependence assumptions: modelled dependence, complete dependence, and complete independence. The modelled dependence assumption mimics the real-world spatial variability of flood peaks and damages across Europe. For each year of the synthetic time series (10 000 years) generated with the copula-based, spatial dependence model, the damage values within the considered region are aggregated. The risk curve of the region is then derived from the empirical cumulative distribution function of these aggregated damage values. Hence, the damage values are directly used to calculate exceedance probabilities, or return periods, shown as regional risk curves in Figs. 4.3 and 4.4. This step, i.e. the derivation of the risk curves, is performed in the same way for the other two scenarios. However, for the complete dependence and complete independence scenarios, the simulated spatial correlation is destroyed before aggregating the catchment damage values to regional values. For the complete dependence scenario, it is assumed that in a given year each river station experiences a flood with the same return period at the respective discharge gauge. To this end, the damage values at each gauge are ranked according to their magnitude, and then aggregated for each year. The complete independence scenario assumes that there is no spatial correlation between the flood magnitudes at different stations. Hence, the damages for the 10 000-year time series at each river station are independently shuffled before aggregation. Because this regional estimate depends on the shuffling, we repeat this procedure 100 times. To represent the risk curve, we use the median of the 100 realizations.

Regional flood risk curves are calculated for three dependence models (Gaussian and Student-t copulas, the latter with two variants regarding the number of degrees of freedom), for three regions (the UK, Germany and Europe) and for two protection scenarios (with and without flood protection). The tail dependence affects only the regional risk curves of the modelled dependence assumption, but has no influence on the risk curves for the complete dependence and complete independence assumptions. For the special case, where one is only interested in the EAD, the spatial dependence can be ignored (Metin et al., 2020). The scenario without flood protection gives an estimation of the maximum damage under failure of all flood protection measures. Although this scenario grossly overestimates the risk, it indicates the exposed assets protected by flood defences. The scenario with flood protection provides the damage when the flood defences work up to their design levels. Flood protection levels are taken from Jongman et al. (2014).

4.3. Results and Discussion

4.3.1. Evaluation of the multivariate dependence model

Annual maximum streamflow (AMS) series at 379 gauging stations (Fig. 4.1a) are extracted from the observational data for the period 1968-1999. These series are used to construct the copula-based multivariate model. The Student-t copula is parameterized using the (379 x 379) correlation matrix and the number of degrees of freedom *df*. The estimated value (*df* = 11.4) indicates a moderate tail dependence in the AMS dataset. The pairwise correlation between AMS series, quantified by Kendall's tau, varies between -0.557 and 0.982 with a rapid decline with distance (Fig. 4.1c). However, there are pairs of stations which are significantly correlated even though they are up to 2000 km apart. The pairwise correlations are visualized exemplarily for nine selected stations (Fig. 4.1a). We use the Student-t copula model to generate 10 000 years of synthetic AMS series. The agreement between simulated and observed correlation is very good (Fig. 4.1b and 4.1c).

We fit the Gumbel and the GEV (Generalized Extreme Value) distribution to the observed AMS series at the 379 locations (Methods). Two goodness-of-fit tests, Anderson-Darling and Cramer-non Mises, indicate very good fits to the observed AMS series (Supplementary Fig.4.1). The multivariate dependence model, i.e. the combination of copulas and marginal distributions, shows good agreement with observations. Fig. 4.2a shows a plausible range of the maximum simulated peak flows over 31-year period at most gauging stations as 87% of confidence range bars cross and the rest deviates slightly from the identity line. Also, the flood frequency curves derived from observed and synthetic discharge correspond well, with the observed flood frequency curves mostly located within the 95% confidence bounds of simulated curves (Fig. 4.2b).

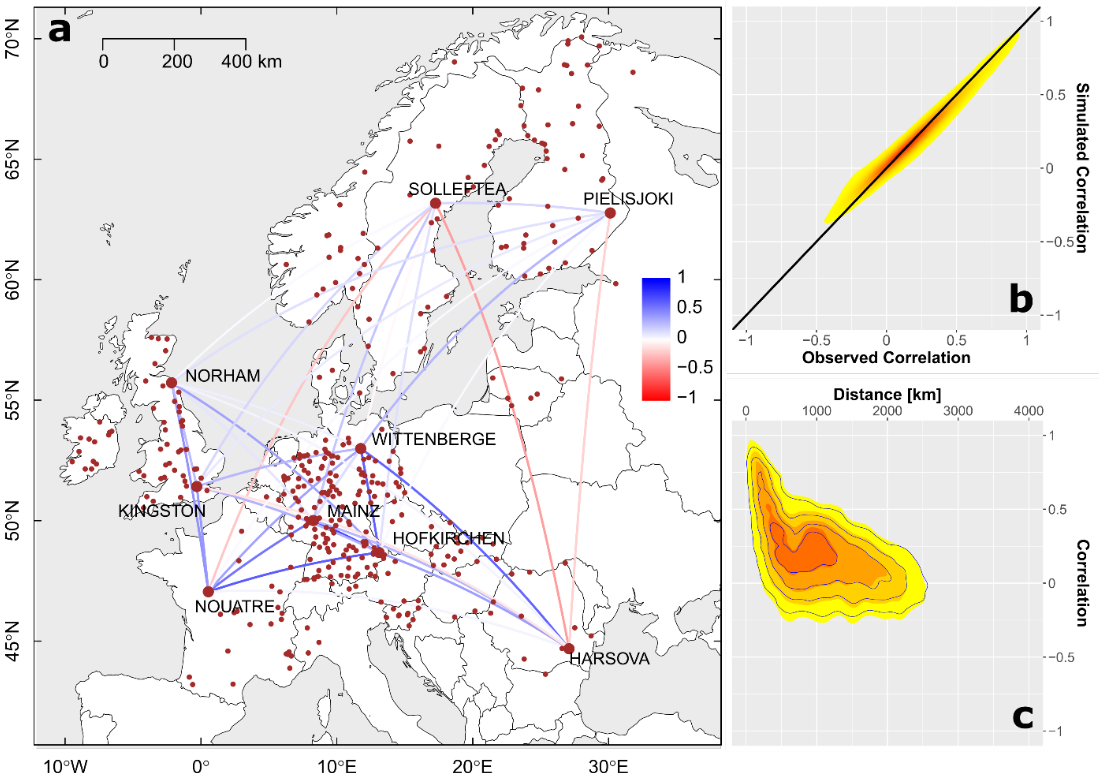


Figure 4.1: Study area and dependence structure **(a)** with locations of 379 gauging stations (red dots) and pairwise correlation (coloured lines) of nine selected stations over Europe; **(b)** Comparison of observed and simulated correlation for all stations. Note the increase of density from yellow to red; **(c)** Correlation versus distance between stations, i.e. correlogram, for observed data (density increases from yellow to red) and simulated data (contour lines); **(b-c)** Simulated values are generated by the Student-t copula with *df*=11.4. All figures created in this chapter are based on the free software environment R for statistical computing and graphics (https://www.r-project.org/).

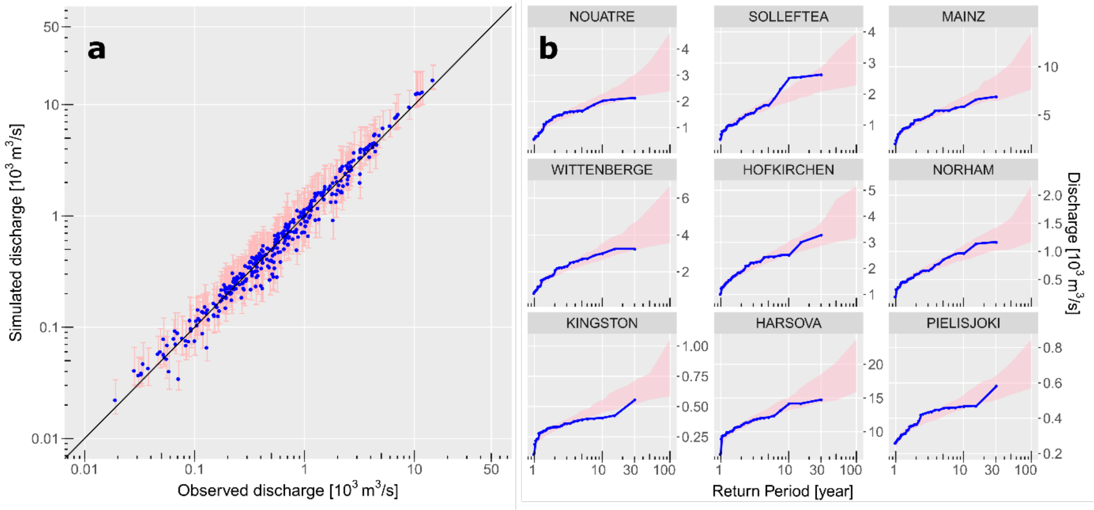


Figure 4.2: Evaluation of the multivariate dependence model **(a)** Maximum observed versus simulated peak flow over 31-year period at all stations. Blue dots represent the median of the pink 95% confidence range corresponding to 322 model realizations of 31 years length. Black line represents the identity (1:1) line. **(b)** Flood frequency for nine selected stations (see location in Figure 4.1): observations (blue curves) and 95% confidence range (shaded ribbons) corresponding to 100 model realizations of 100 years length.

4.3.2. Risk estimates for the three dependence assumptions

The regional risk curves, i.e. the relation between aggregated flood damages and return periods for the considered regions, are strongly affected by the dependence assumption (Fig. 4.3). The complete dependence assumption overestimates regional flood risk for large return periods but underestimates risk for small to medium return periods. The shift from underestimation to overestimation, in the following termed the intersection point, occurs roughly around the flood protection levels, i.e. between return periods of 80 to 120 years for the three regions. The misestimation of risk is explained by the assumption of homogeneity. The complete dependence assumption assigns the same return period discharge peaks to all gauges and to corresponding damages in the adjacent areas. If this return period is smaller than the flood protection level for all (or most of the) areas, the aggregated damage for the region is zero (or small). If it is higher than the protection level, on the other hand, it causes damages in all areas as the protection is overtopped throughout the region. In reality, represented by the modelled dependence assumption, the spatial variability of flood peaks causes damages at some locations even when the regional return period of this event, i.e. the return period of the total aggregated damage, is clearly below the protection level (Supplementary Fig.4.2). Hence, the spatial variability leads to a smoothly increasing regional risk curve, compared to the rather threshold-like curve for the complete dependence assumption. The bias by the complete dependence assumption is substantial (Fig. 4.3). For the 200-year return period, damage is overestimated by 139%, 188% and 246% for the UK, Germany and Europe, respectively. The 50-year damage is underestimated by 93%, 69% and 42%, respectively. The intersection points between the complete independence and the modelled dependence curves have the return period of 38, 15 and 12 years for three regions respectively. The risk curve of the complete independence behaves differently as it shifts from overestimation to underestimation of flood damage at the intersection point compared to modelled dependence moving from low to high return period level. The 200-year flood damage is underestimated by 27%, 60% and 61%, respectively, for the three regions. The regional 50-year damage is still underestimated by 12%, 48% and 52%. However, the 10-year damage is found to be overestimated by 75%, 69% and 14% respectively.

Alfieri et al. (2015a) estimate the economic damage for the 100-year flood event as EUR 1.5 billion for the UK, EUR 15 billion for Germany and EUR 120 billion for Europe. Our estimates are somewhat higher at the national scale (EUR 2.6 billion for the UK, EUR 20 billion for Germany), but much lower at the continental scale (EUR 52 billion for Europe). The grid-based simulation model of Alfieri et al. (2015a) considers entire Europe, whereas our estimate is limited to the catchments associated with the 379 gauges. Since many areas in Europe are not covered by observational data in GRDC (2020), our regional risk estimates consider only part of the entire area for the UK, Germany and Europe, respectively. For the UK and Germany, where we have a high density of stations, our estimates are much closer to the results of Alfieri et al. (2015a).

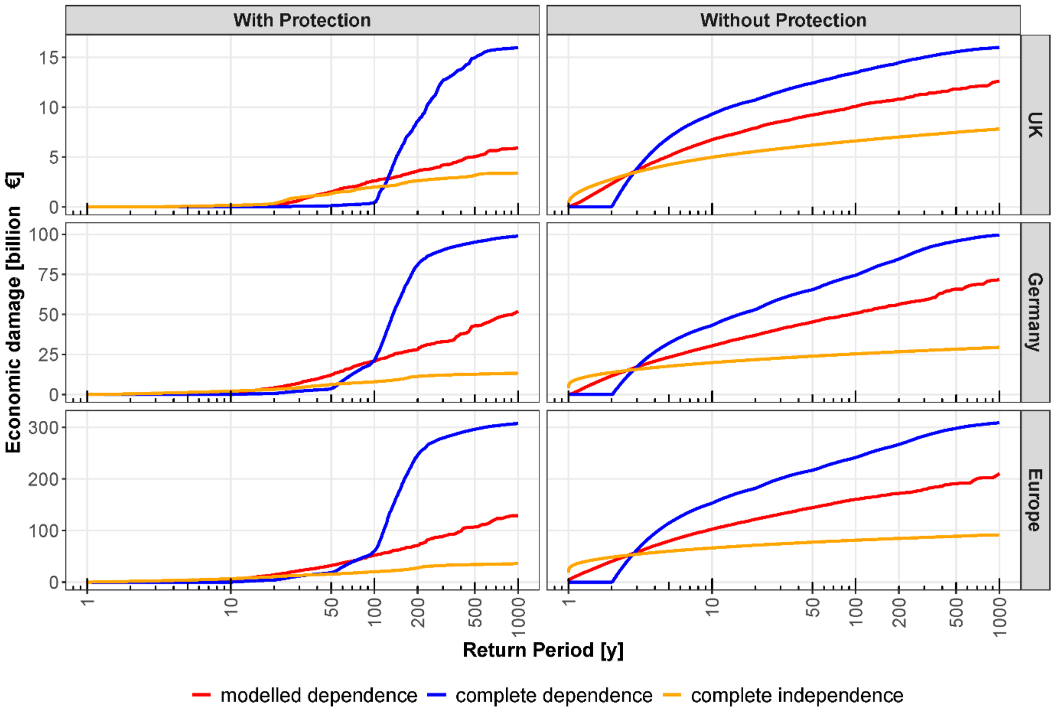


Figure 4.3: Regional risk curves, i.e. flood damages and their corresponding return periods under the assumptions of complete dependence, modelled dependence and complete independence for the UK, Germany and Europe for the scenario with flood protection and without flood protection.

The main influence on the intersection point, i.e. where underestimation turns into overestimation for the complete dependence assumption, is the flood protection level (Fig. 4.3). For a scenario without protection, the intersection point corresponds to a return period of 3 years. The damage model assumes that there is no damage for discharge peaks below the 2-year flood, which is a good proxy for bankfull conditions (Carpenter et al., 1999). Hence, the risk curves for the complete dependence assumption show damages only for events larger than 2 years. In contrast, the modelled and complete independence assumptions estimate damage also for the 2-year return period, as the spatial variability causes some locations to have peaks higher than the 2-year flood.

4.3.3. Effects of tail dependence on regional risk estimates

To understand how the tail dependence affects the regional risk estimates and the biases of the different dependence assumptions, we fit two additional copula models to the AMS data: The Gaussian copula, which does not include tail dependence, and the Student-t copula with *df*=4. This value is chosen to represent strong tail dependence. A stronger tail dependence leads to higher damage estimates for large return periods, moving the regional risk curve of the modelled dependence assumption closer to the complete dependence assumption (Fig. 4.4). For the 200-year regional damage, for instance, the overestimation of 139%, 188% and 246% for the UK, Germany and Europe is reduced to 113%, 140% and 180%, respectively, for the scenario with strong tail dependence and increases to 171%, 240% and 298% when removing the tail dependence by assuming the Gaussian copula.

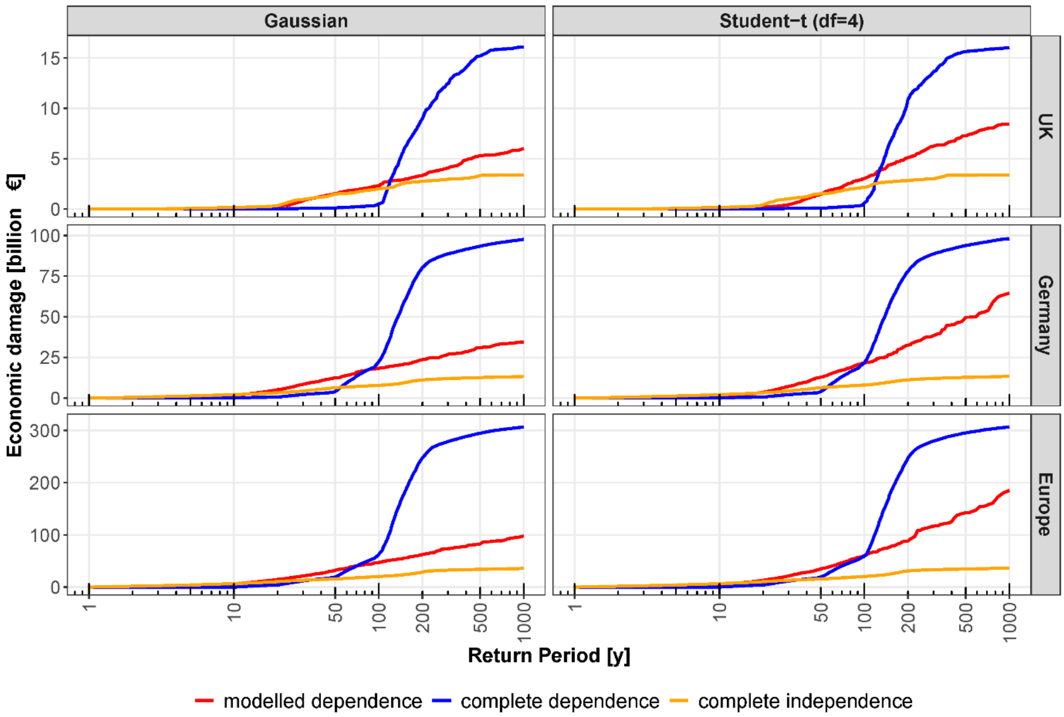


Figure 4.4: Influence of tail dependence on regional risk curves, i.e. flood damages and their corresponding return periods for the UK, Germany and Europe for the three dependence assumptions. The Gaussian copula does not include tail dependence, while the Student-t copula with *df*=4 represents rather strong tail dependence.

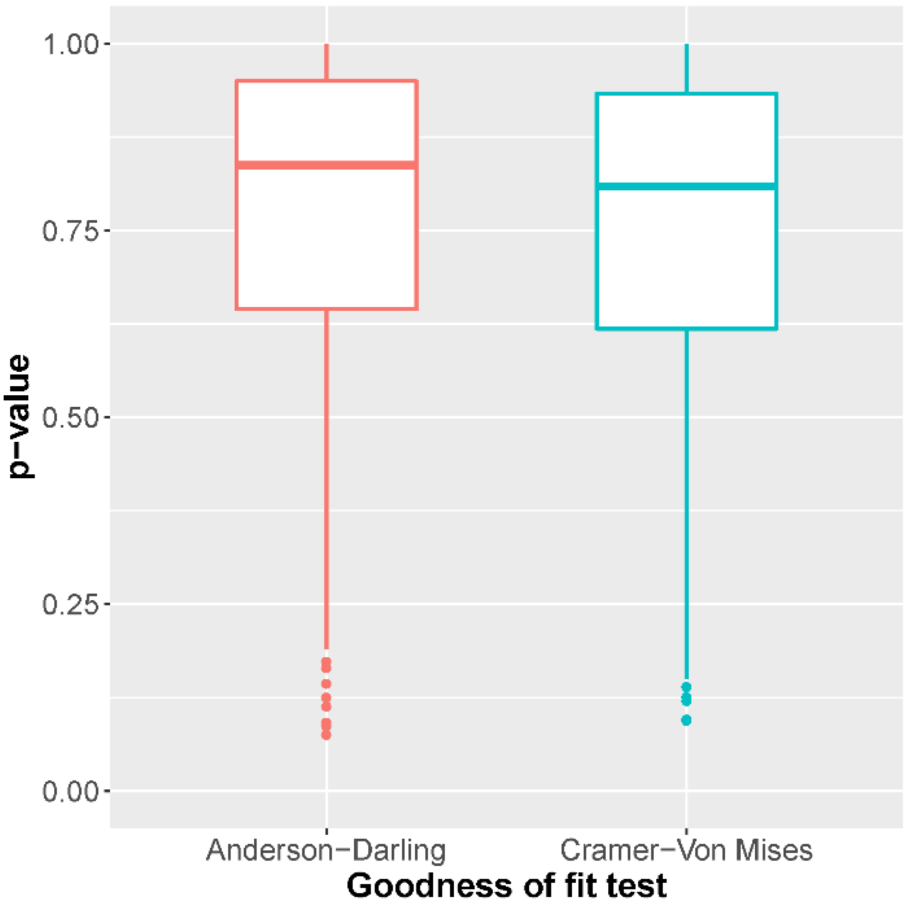
4.4. Conclusions

The study highlights a potential misestimation of flood risk at national and continental scales. We find that the widespread homogeneity assumption overestimates the regional 200-year damage, which is a benchmark indicator for the insurance industry, by 139%, 188% and 246% for the UK, Germany and Europe, respectively. For small return periods, it underestimates flood risk. The intersection point, where underestimation turns into overestimation, depends on the threshold beyond which damages steeply increase, i.e. on the flood protection level. We further show that tail dependence can substantially influence regional risk estimates. The numbers suggest that the misestimation increases with increasing spatial scale. Hence, our study demonstrates the importance of including the spatial dependence of flood peaks and particularly of tail dependence in national and continental risk assessments.

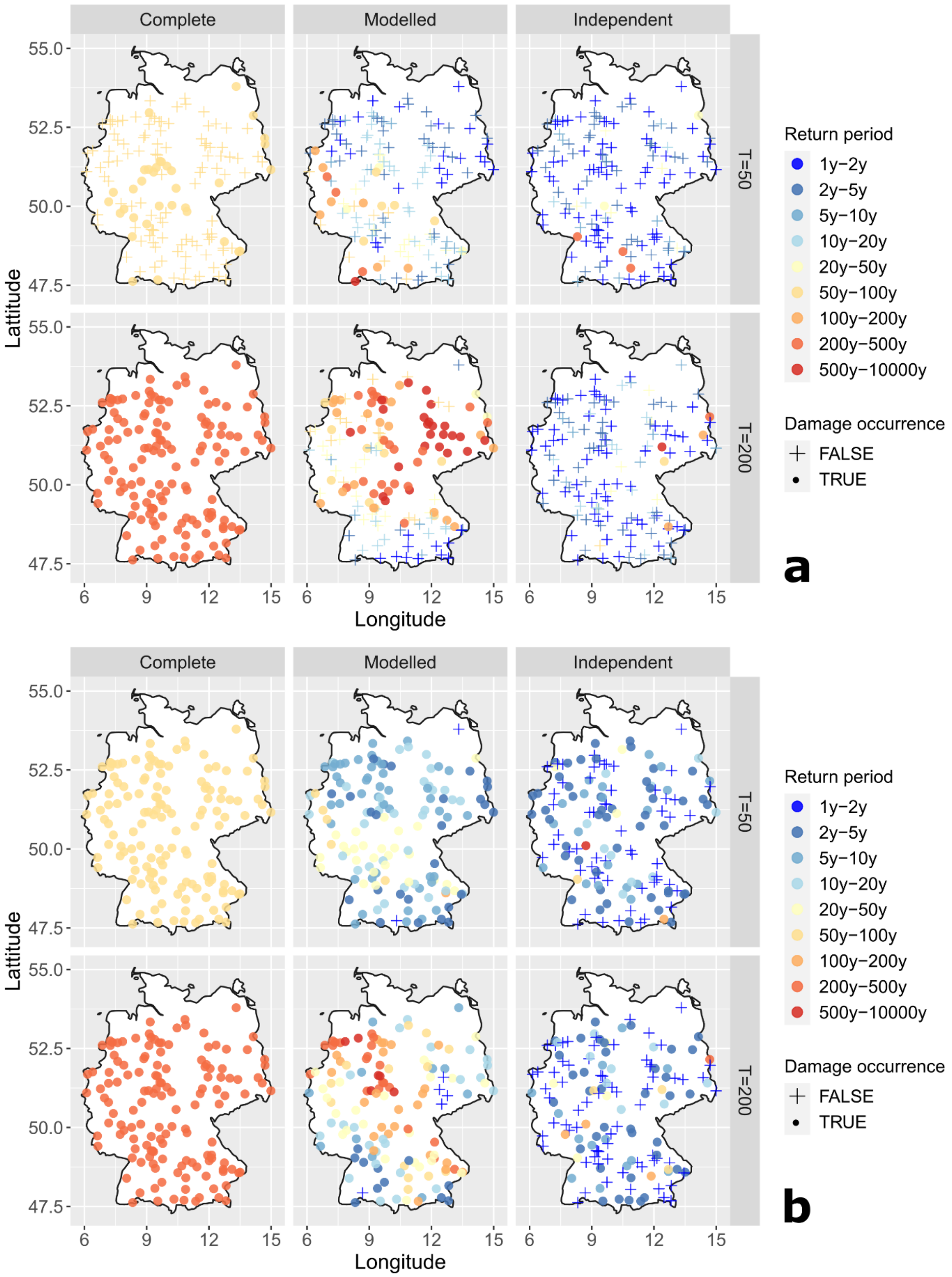
Data availability

The GRDC discharge dataset was obtained from the Global Runoff Data Centre, 56068 Koblenz, Germany (https://www.bafg.de/GRDC/EN, last access: October 2017) and was recently made available for online download via https://portal.grdc.bafg.de. Flood hazard maps for the European Union can be downloaded from http://data.jrc.ec.europa.eu/collection/floods. Flood protection levels are taken from Jongman et al. (2014).

4.S. Supplementary for Chapter 4



Supplementary Figure 4.1: p-values of goodness-of-fit tests for fitting the distribution (Gumbel/GEV) to the AMS data. The null hypothesis H_0 is that the data follow the distribution. The alternative hypothesis H_a is that the data do not follow the distribution. The significance level is set at 0.05.



Supplementary Figure 4.2: Spatial distribution of the return period of loss for Germany under the three assumptions: complete dependence, modelled dependence and complete independence. Two return period levels T = 50 years (small) and T = 200 years (high) are selected for illustration; **(a)** Scenario with flood protection; **(b)** Scenario without flood protection.

Chapter 5 – Synthesis

5.1. Findings of this thesis

In this thesis, the main objective is to understand the impact of changes in flood risk components and the importance of spatial dependence in flood risk estimations. Chapter 2 aims to overcome the problem of lacking comprehensive studies that consider the entire spectrum of drivers to understand change in flood risk. Therefore, a sensitivity analysis is conducted to quantify the sensitivity of flood risk to changes along the risk chain considering continuous simulation of this chain. Chapter 3 and 4 aim to illustrate the misestimation in risk under the false assumptions of spatial dependence at different spatial scales. Chapter 3 quantifies this misestimation using continuous simulation of flood risk for the Elbe catchment. Chapter 4 applies multivariate dependence model based on flood discharges over national (United Kingdom and Germany) and continental (Europe) scales and highlights the misestimations in risk. The key findings obtained from three main chapters are listed below. In this section, main outcomes are summarized with respect to the specific research questions framed in the introduction chapter.

Key findings

⇒ The adverse impact of climate change on flood risk can be masked by dike heightening or reduced vulnerability such as high level of uptake of precautionary measures.

⇒ The impacts of change in catchment hydrology, in river system, and in land use can show variability across catchment upstream and downstream.

⇒ Climate change impact can be significant for certain seasons where large variations in precipitation are observed.

⇒ The assumption of homogeneous return period scenarios in the Elbe catchment can cause up to 100 % overestimation in economic damage for large return periods.

⇒ The discrepancy between the risk curves of homogeneous return period (complete dependence) and heterogeneous return period (modelled dependence) scenarios may increase with an increasing spatial scale.

⇒ Flood risk can be overestimated by 139 %, 188 % and 246 % for 200-year return period in UK, Germany (national scale) and Europe (continental scale), respectively.

⇒ There is also an underestimation under the assumption of complete dependence for smaller return periods.

⇒ The Expected Annual Damage (EAD) does not differ too much under the different spatial dependence assumptions.

⇒ The risk estimation under the consideration of spatial dependence can be affected by the structural flood protection level and copula-based multivariate model.

❖ How and to what extent do the changes in risk components propagate through risk chain and affect flood risk?

To evaluate the propagation of changes in risk components and its influence on overall flood risk, a comprehensive sensitivity analysis is performed in Chapter 2. In this comprehensive analysis, changes in all risk components, i.e. changes in climate, catchment, river system, land use, assets, and vulnerability are considered for the mesoscale Mulde catchment in Germany. For each component, a baseline and two symmetric change scenarios within a range of plausible values are created and combined for six components leading to 729 scenarios in total. Each of these scenarios contain 4000-year continuous simulation of risk chain. The results are indicated by two risk indicators: risk curve and EAD. The first outcome of this sensitivity analysis is that the change in river system (dike heightening) has the largest contribution to flood risk change (strong reduction in EAD). Besides, maximum EAD values are always obtained with low dike height scenarios. On the other hand, climate change shows the minimum contribution among the other risk components, although it is often addressed as the most influential component. Further, decrease in the reservoir capacity of the catchment increases risk substantially. However, increase in the reservoir capacity do not reduce risk significantly because the damage mostly occurs at other locations within the catchment. The changes in assets, land use and vulnerability show similar impact on flood risk changes and these impacts are significant.

The relative effects of various risk components on overall risk are also investigated in Chapter 2. By selecting a subset of change scenarios, the combined or opposed influences of risk components are analysed. It is concluded that the effect of climate change can be compensated by all other risk components except for change in reservoir storage capacity where the most compensation is observed by dike heightening. With a selection of different sets of scenarios, the interaction between climate change and the change in land use and vulnerability, by allowing only increase in asset values, is investigated. It is perceived that under the climate change scenario, the range of EAD can be capped between EUR 0.5 million to EUR 2 million, by altering only land use and vulnerability. With this outcome, it can be inferred that the effect of climate change and increasing asset values on flood risk can be counteracted using measures other than structural protection.

❖ How is the overall flood risk affected by the changes in risk components for different locations and seasons?

For a better understanding of the effect of changes in risk components at different locations, all possible change scenarios are analysed for selected upstream (Zwickau) and downstream (Anhalt-Bitterfeld) sub-basins in the catchment. The impacts of change in climate, asset values and vulnerability upstream and downstream are similar to the impacts in the entire catchment. However, the impacts of change in flood storage capacity, river system and land use show some differences upstream and downstream. Regarding the change in reservoirs, most of the reservoirs are located upstream of the catchment and the largest reservoir is located upstream of the reach around Zwickau. Hence, doubling of reservoir storage capacity has only minor impacts on the downstream risk for very large events. Change in river system shows different behaviour upstream and downstream. This is explained by the impact of topography on the number of exposed asset values. For instance, steep upstream and flat downstream regions are affected differently given the same magnitude of flood event. Different land use scenarios also cause different behaviour upstream and downstream. The increase in residential areas results in higher risk upstream for frequent flood events, but at the downstream region, it increases risk for extreme events. The change in risk upstream under the different land use scenarios is mainly explained by the reservoir operation rules. Since reservoirs start to operate above the 100-year discharge, they cannot affect flows for frequent flood events. When the operation starts, risk becomes similar for different land use scenarios. On the other hand, the change in risk downstream for different land use scenarios is explained by the topography and specific set-up of residential buildings. For instance, additional residential areas in land use scenarios might not be exposed to floods. Also, if the residential buildings are located at steeper areas, they are not exposed to floods.

To understand the effect of changes in risk components during different seasons, all scenarios concerning components of atmosphere, catchment and river system are analysed for winter and summer seasons. The effect of change in atmosphere is significant in the winter season because of the large variation in precipitation values. The change in catchment system primarily contributes to risk for return periods higher than 500-year in winter, and for the return periods higher than 100-year in summer. This is mainly explained by the reservoir operation rule and the magnitude of events in different seasons. Finally, the risk curves under the change in river system show similar patterns and great importance for both seasons.

❖ **What is the bias in risk estimates under the 'false' assumptions of spatial dependence of return periods of damages?**

To investigate the bias in risk estimates under the false assumptions of spatial dependence, first, real spatial and temporal dependencies are approximated by 10 000-year continuous flood simulation. This modelled dependence assumption (heterogeneous return periods) is compared with the false assumptions of spatial dependence: complete dependence (homogeneous return periods) and complete independence (randomly sampled return periods) for the Elbe catchment in Chapter 3. This comparison revealed that the flood damage is vigorously overestimated (up to 100 %) by the widely used assumption of complete dependence for return periods higher than 200 years in the Elbe catchment. On the other hand, for return periods smaller than approximately 90 years, flood damage is underestimated under the assumption of complete dependence. In addition, under the assumption of complete independence, there can be up to 50 % underestimation indicating the lower limit for the damage estimations for large return periods.

The investigation of the role of spatial dependence in the large-scale risk assessment is extended to European scale in Chapter 4. Since implementing continuous modelling for such a large scale is challenging, copula-based multivariate dependence models are used to compare three assumptions on spatial dependence. The modelled dependence is based on the spatial dependence of annual maximum series of discharge data across 379 gauging stations over Europe. One of the important outcomes from Chapter 4 is that under the assumption of homogeneous return periods, there is a possibility of overestimating risk in Europe by 246 % for the 200-year return period of event. The lower limit for the risk estimates for the same return period of event is determined by the assumption of complete independence and results in approximately 60 % underestimation.

If the risk is represented by the EAD, Chapter 3 confirms that spatial dependence can be neglected. The reason for this is that the damages are averaged and weighted by their probabilities. Therefore, EAD does not depend on the assumed dependence scenario.

- **What is the role of spatial scale, tail dependence in the multivariate dependence model and structural flood protection level on flood risk under the different assumptions of spatial dependence?**

The variation in risk estimates with an increasing spatial scale is investigated by aggregation of the risk curves from upstream regions to the entire catchment. In Chapter 3, for the three spatial dependence assumptions risk curves are obtained at 12 different spatial scales by aggregating sub-basins from upstream to downstream. Remarkably, under three assumptions, the discrepancy between the risk curves increases with increasing scale. As is well known, the spatial dependence of damage in smaller areas is often stronger. Hence, not much difference is expected between the risk curves of complete dependence and modelled dependence. However, the model dependence curve shifts toward complete independence curve with increasing scale.

The risk estimations under the three assumptions on spatial dependence are compared by considering different spatial extents, multivariate dependence models for Gaussian and Student-t copulas and different levels of structural flood protections in Chapter 4. For a better understanding of the role of spatial extent on risk estimation, results are provided for two national scales (UK and Germany) in addition to continental scale risk analysis. Only slight differences are observed in overestimation at three different spatial extent and overestimation changes between approximately 135 % and 250 % for 200-year return period at both national and continental scales. No clear trend of the impact of spatial extent on flood risk was detected.

To understand the role of tail dependence, results with Gaussian copula (tail independent), fitted Student-t copula (moderate tail dependence) and Student-t copula with low degree of freedom (strong tail dependence) are compared. Tail dependence indicates the dependence between damages of extreme events. As expected, under the consideration of strong tail dependence, modelled dependence risk curve shifts toward the complete dependence curve. Therefore, while overestimation reduces under complete dependence, underestimation increases under complete independence.

The impact of flood protection on risk under three spatial dependence assumptions is investigated by comparing the resulting damages with and without flood protection. The overestimation increases if flood protection is considered. For instance, there is up to 50 % overestimation in economic damage under no flood protection. However, damage is overestimated by up to 246 % in Europe for the existence of flood protection. This is because some frequent events up to the level of flood protection are prevented. Therefore, total damage is reduced at each return period in the presence of flood protection. On the other hand, the point where underestimation turns to overestimation (so-called intersection point) is observed at around 3- and 100-year return periods under without and with flood protection conditions, respectively. Since no damage is observed up to level of protection, overestimation starts only when flood events start to exceed the protection level. Therefore, intersection point is strongly dependent on the level of flood protection.

5.2. Discussion and recommendations

In Chapters 2 and 3, continuous flood risk modelling with different modules is implemented and used. Each of the modules have their own limitations and uncertainties which might add up or overlap through the model chain. For instance, it is challenging to capture spatial dependence of precipitation for a weather generator. Spatial dependence of high precipitation can be overestimated because of the isotropic covariance function (Serinaldi and Kilsby, 2014) in the used auto-regressive model. This may result in highly dependent discharge peaks. Besides this, although hydrological model SWIM shows reasonable discharge estimations, discharges may be overestimated at few mountainous locations such as upstream of the Saale catchment due to the consideration of daily-scale flood processes instead of hourly scale. In fact, at some locations travel time of the flood peaks can be shorter than a day. This presumably causes an overestimation of inundation extent estimated by the hydraulic models. On the other hand, the inundation extent can be underestimated at some other regions due to neglected dike breaches in the hydraulic processes. These are some of the important limitations of the model. Although simulations of dike breaches increase the computation time enormously, it is recommended to implement a probabilistic approach for dike breaching for more accurate damage results. In addition to uncertainties coming from these modules, the damage model also contains uncertainties in exposure and vulnerability estimates. Therefore, large errors may be prevalent in the damage estimations.

The study investigated in Chapter 2 is the most comprehensive sensitivity analysis which considers entire range of flood risk components with the continuous modelling approach. However, this analysis is limited to three change scenarios for each risk component. The change in risk highly depends on these scenarios. Although the scenario selection is subjective, the best available data and options are used. For example, river system scenarios are created based on the possible changes in dike heights taken from the literature. Besides, scenarios of change in climate, reservoir storage capacity, land use and asset values are created based on historical data. Nevertheless, some increase scenarios might not hold in the real world. For example, changes in precipitation and temperature will probably be different due to human-induced climate change. Similarly, increase in land use may vary in reality. Notwithstanding the subjectiveness in some of the scenarios, the sensitivity analysis provides a better perception of risk and risk reduction measures by considering the entire range of risk components. Since the aim of Chapter 2 is not to evaluate the exact damage values under different scenarios, the assumptions are acceptable for performing a sensitivity analysis.

Chapter 2 provides an insight into the possible risk reduction measures going beyond structural flood protection measures which are not always feasible options. For instance, dike heightening along the river network can be very expensive. In addition, construction of structural measures can pose some threats to the ecosystem. Therefore, alternative risk reduction measures are of great importance in flood risk assessment and management. The sensitivity analysis in Chapter 2 shows that, in addition to dike heightening, changes in land use and vulnerability can also mask adverse impact of climate change and reduce flood risk. Vulnerability reduction is more feasible than change in settlement areas (relocation) as it requires considerable period of time. However, the sensitivity analysis in this thesis only focuses on changes in private precautionary measures as vulnerability scenarios. However, vulnerability scenarios can be influenced by awareness and preparedness, as well. A reasonable explanation for this is that mainly precautionary measures were taken by private households and companies in Germany between hazardous flood events in 2002 and 2013. Nevertheless, the impact of other risk reduction measures which reduce the vulnerability (e.g. risk awareness, flood early warning) should be included with more specific assumptions for different regions to elaborate the understanding of risk and risk reduction measures in future research. Additionally, since vulnerability reduction is a great alternative to reduce flood risk, it should definitely be considered in risk assessment and management.

The spatial variability in return periods of floods is often considered by multivariate statistical models where the spatial dependence of flood peaks is considered in the literature. In order to simulate inundated areas, the entire hydrograph (e.g. shape, duration and volume) is required. However, in this approach, flood hydrographs are not mass conservative since only flood peaks are considered. Therefore, this approach may result in some uncertainties and errors.

In Chapter 3, on the other hand, the spatial variability is considered by end-to-end flood risk assessment. The bias in risk is estimated by considering the spatial dependence of all processes along the risk chain. This approach requires high computational time but it is advantageous as the complete flood event throughout the entire catchment is modelled in a consistent way, including antecedent processes. Therefore, the study in Chapter 3 provides a more realistic representation of the spatial dependence throughout a river basin.

Chapter 3 allows for understanding the variations in risk estimates with different spatial scales from upstream to downstream. For smaller upstream areas, the risk curves under complete and modelled dependence assumptions tend to be similar. The risk estimation under complete dependence becomes larger than the modelled dependence and the difference between modelled dependence and independence curves decreases with increased spatial scale. Yet, these variations with increased scale can be vague and different processes of damage generation mechanisms such as catchment topology, structural flood protection, flood wave superposition and spatial distribution of the assets and their vulnerability can blur the impact of increasing spatial scale. Therefore, further analysis on the impact of spatial dependences of different damage-generating processes on the risk estimates is recommended. This may aid in understanding the contribution of several damage-generating processes and thereby helps to decide which processes needs to be considered or can be neglected in a general way.

In addition to the variability in risk estimates, the intersection point shifts from return period of few hundred years to nearly 90 years with increasing spatial scale. Although, intersection point is primarily affected by the damage threshold (i.e. level of flood protection), this change in intersection point is not a consequence of different flood protection standards in the up- and down-stream of the Elbe catchment. This is likely caused by the modelling and data errors. The small-scale variability of precipitation extremes is insufficiently captured by the weather generator in some sub-basins due to varying station density used for parametrization. Consequently, damage is underestimated for the Mulde and Black Elster rivers and is overestimated for the Saale River.

If the main concern is the expected annual damage (EAD) in flood risk assessment, the spatial dependence does not bias its estimate (Chapter 3). The EAD is the sum of the damages weighted by their probabilities for each sub-basin in the Elbe catchment. Since the mean value of a sum of random variables is not affected by the correlations between the variables, the spatial correlation is not significant while calculating EAD. Therefore, the EAD does not differ under both complete and modelled dependence assumptions. However, the EAD is a rather limited measure of risk (e.g. Merz *et al* 2009). Flood risk assessment and management may require specific risk scenarios for different purposes where spatial dependence is crucial. According to Article 101 of the European Solvency II Directive (EC, 2009), it should be proved that at least damage events with 200-year return period is covered by insurance companies. Therefore, it is crucial to include the 'true' spatial dependence pattern in the risk analyses.

For an improved understanding of the role of spatial dependence, Chapter 4 compares three spatial dependence assumptions at larger scales, including the role of tail dependence and flood protection. Tail dependence might be of great importance in flood risk assessment. Because tail dependence indicates the dependence between extreme events, the small and large differences between the risk curves under complete and modelled dependence assumptions are expected for high and low tail dependence, respectively. Since the risk curve under modelled dependence changes with respect to the complete dependence risk curve, the intersection point can also be affected by tail dependence. Nevertheless, the impact of tail dependence on the intersection point is small and hence this impact is of minor importance.

The flood protection level substantially influences risk estimation and intersection point. In the presence of structural flood protection, many frequent and low-magnitude flood events are prevented. Therefore, the damage estimation is rather smaller in the presence of flood protection compared to no flood protection.

With no flood protection, there is no damage under 2-year return period because it represents bankfull discharge condition. When flood protection is considered, no damage is observed up to the corresponding protection level. Under the assumption of complete dependence, all stations are assumed to experience homogenous return period of damage. Therefore, there is no damage up to 2-year return period without flood protection and there is no damage up to mean protection level with flood protection. However, under the assumptions of modelled dependence and complete independence, due to heterogenous return period of damage within the region, damages may still occur below flood protection level. On the other hand, above this level, damage under the complete dependence assumption becomes larger than the damages under modelled dependence and complete independence.

The mean flood protection level can be different from country to country. For example, the mean protection level in UK is mostly higher than in Germany (Gall and Gerber, 2014). Accordingly, compared to Germany, the intersection point is observed at higher return periods in UK in Chapter 4. Yet, the relation between flood protection level and intersection point should be treated with caution since the information on flood protection standards is globally limited whilst estimating flood risk (e.g. neglected protection standards or crude assumptions on flood protection levels).

5.3. Conclusions

This thesis has improved the understanding of the role of various risk components on flood risk. The sensitivity analysis with continuous simulation approach reveals that flood risk can vary widely across the range of all possible change scenarios, within a few decades. The risk is strongly sensitive to change in structural protection level and less sensitive to climate change. The uncontrolled risk components, such as climate change and increase in asset values, can be masked by risk components which can be controlled. This provides options for local stakeholders to control the increasing flood risk due to climate change and economic growth by flood risk management. The technical flood protection measures are often devised to reduce flood risk. However, not only river system changes but also changes in land use and vulnerability can diminish the adverse impact of climate change. This outcome proves the role of alternative risk mitigation measures such as reduced vulnerability with high level of private precaution instead of taking structural protection measures. Also, the importance of an integrated analysis of risk components to combat flood losses in the risk management is highlighted.

The sensitivity of flood risk to each risk component can vary for different regions and seasons. The main reasons for this variation are the different topographies and the uneven distributions of reservoirs and residential buildings within the catchment. Therefore, the role of change in reservoirs, protection levels and land use on flood risk are different for upstream and downstream of the Mulde catchment. Besides, the change in the impacts of risk components for the different seasons is attributed to the large differences in precipitation and temperature for winter and summer seasons. Although floods are frequent in winter, the most extreme ones have occurred in summer. Furthermore, climate change impacts manifest itself for high-probability events due to strong increase in precipitation in winter and almost no change in summer. It should be noted that spatial and temporal variations can strongly influence the impacts of risk components and therefore it is crucial to consider them during risk assessment.

The misestimation of spatial variability in return periods of floods can cause bias in large scale risk assessment. One of the best ways to consider spatial variability is continuous hydrological-hydrodynamic simulation. The advantage of this approach is that all hydrological processes which affects the runoff are implicitly considered and the entire flood event is modelled including antecedent catchment processes. However, it is computationally expensive, and may not always be applicable. For this reason, while continuous modelling approach is used for the Elbe catchment, copula-based multivariate dependence model is developed for the European scale. It is also reasonable approach to consider heterogeneity in the catchment where it relies on the spatial dependence between discharge peaks at multiple sites.

When spatially homogeneous return period (complete dependence) scenarios are assumed, damage is always computed larger than the heterogeneous return period (modelled dependence) scenarios for high return periods (i.e. beyond the intersection point) of events. This overestimation reaches up to 100 % in the Elbe catchment, 139 % in UK, 188 % in Germany and 246 % in Europe. On the other hand, the complete dependence scenarios estimate smaller damage than the modelled dependence scenarios for events with small to medium return periods. The influencing factors of the intersection point where the underestimation turns to an overestimation are further investigated and it is found that the flood protection level plays a significant role on the intersection point.

The misestimation of risk may also differ for the upstream and downstream areas within the catchment. The modelled dependence assumption is closer to complete dependence for the upstream areas of the Elbe catchment. This implies that for small spatial scales, complete dependence assumption is appropriate. However, with an increasing spatial scale towards downstream, modelled dependence assumption is closer to independence assumption. This is due to the higher heterogeneity in large spatial scales for a single flood event. Yet, more systematic analysis is required to derive a general statement about the precise scales where certain assumptions might serve as an approximation.

In the multi-variate dependence model, the risk estimation under modelled dependence is heavily impacted by the tail dependence. The discrepancy between the risk curves under the complete dependence and modelled dependence assumptions can vary for different copulas. The modelled dependence is closer to complete dependence when copula with high tail dependence is considered. This highlights the importance of the reliable estimation of the tail dependence while representing spatial dependence in the risk assessment. Besides, the consideration of flood protection level substantially affects risk estimation and the discrepancy between complete and modelled dependence assumptions is high in the presence of flood protection.

If the risk is only expressed with expected annual damage (EAD), the risk estimates are similar under the assumptions of both complete and modelled dependence. However, this is not surprising since EAD is a mean value of damages and is not affected by the correlations between variables. Yet, I strongly recommend to consider complete risk curves since it offers more broader perspective on risk and impacts of mitigation measures. For complete risk curves, the consideration of spatial dependence of return periods has utmost importance.

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