Cumulative Dissertation

Reliability of Flood Damage Estimations across Spatial Scales

for the degree of
doctor rerum naturalium
(Dr. rer. nat.)
in Natural Hazards Research

submitted to the Faculty of Science
at the University of Potsdam

prepared at the Section Hydrology
of the German Research Centre for Geosciences (GFZ)

by
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submitted on 27th of September 2018
defended on 22th of February 2019

https://doi.org/10.25932/publishup-42616
https://nbn-resolving.org/urn:nbn:de:kobv:517-opus4-426161

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The past, like the future, is indefinite and exists only as a spectrum of possibilities.

- Stephen Hawking

Declaration of originality

I, Tobias Sieg, hereby declare that, to the best of my knowledge, this work does not bear resemblance to any other work in whole or in part and has been completed by myself. I did not use any other sources and means than specified. Furthermore, this work has not been previously submitted to any university. All sources have been referred to and this work gives adequate credit to others for their work. I, in no way, claim to have created this information myself.

Location and Date	Tobias Sieg

Acknowledgements

Although there is only one name written on the front cover of this thesis, the work was supported by a lot of people in many different ways. Here, I want to take the opportunity to express my deep gratitude.

My deepest gratitude goes to my supervisor Heidi Kreibich for her willingness to discuss ideas and comment on the work at any time. Also, for motivating me and giving me the opportunity to focus on this work.

I am deeply grateful to Bruno Merz for the possibility to pursue this work at the section 5.4 Hydrology at the GFZ. Many of his precise comments improved the studies in many ways.

I thank Matthijs Kok for agreeing to act as an external reviewer on this thesis.

I am especially thankful to Kristin Vogel for fruitful discussions about methodological and non-methodological subjects. Her critical reviewing of the manuscripts was a very helpful contribution.

I want to thank Reinhard Mechler and Thomas Schinko for their supervision during my stay at IIASA and everyone who was involved in the YSSP 2017.

Furthermore, I am very thankful to the editors and reviewers who contributed to the improvements of the manuscripts' quality.

Special thanks go to all members of the graduate school NatRiskChange, in particular to Ugur Öztürk, Georg Veh, Sebastian von Specht, Dadiyorto Wendi, Ankit Agarwal, Jonas Laudan, Irene Crisologo and Viktor Rözer for good times in and outside the office. Furthermore, I want to thank Annegret Thieken and Axel Bronstert as chairpersons for their motivation and support. Also, I want to thank all colleagues in section 5.4 at the GFZ for the warm welcome and the support.

My warmest thanks go to Daniela Kretz for proof-reading large parts of the thesis.

Heartfelt thanks go to my family, for believing in me at any time.

Most importantly, I want to thank my girlfriend Theresa for her understanding, patience, and strength in taking all the strains that certainly came up during the last three years.

Kurzfassung

Extreme Naturereignisse sind ein integraler Bestandteil der Natur der Erde. Sie werden erst dann zu Gefahren für die Gesellschaft, wenn sie diesen Ereignissen ausgesetzt ist. Dann allerdings können Naturgefahren verheerende Folgen für die Gesellschaft haben. Besonders hydro-meteorologische Gefahren wie zum Beispiel Flusshochwasser, Starkregenereignisse, Winterstürme, Orkane oder Tornados haben ein hohes Schadenspotential und treten rund um den Globus auf. Einhergehend mit einer immer wärmer werdenden Welt, werden auch Extremwetterereignisse, welche potentiell Naturgefahren auslösen können, immer wahrscheinlicher. Allerdings trägt nicht nur eine sich verändernde Umwelt zur Erhöhung des Risikos von Naturgefahren bei, sondern auch eine sich verändernde Gesellschaft. Daher ist ein angemessenes Risikomanagement erforderlich um die Gesellschaft auf jeder räumlichen Ebene an diese Veränderungen anzupassen. Ein essentieller Bestandteil dieses Managements ist die Abschätzung der ökonomischen Auswirkungen der Naturgefahren. Bisher allerdings fehlen verlässliche Methoden um die Auswirkungen von hydro-meteorologischen Gefahren abzuschätzen.

Ein Hauptbestandteil dieser Arbeit ist daher die Entwicklung und Anwendung einer neuen Methode, welche die Verlässlichkeit der Schadensschätzung verbessert. Die Methode wurde beispielhaft zur Schätzung der ökonomischen Auswirkungen eines Flusshochwassers auf einzelne Unternehmen bis hin zu den Auswirkungen auf das gesamte Wirtschaftssystem Deutschlands erfolgreich angewendet. Bestehende Methoden geben meist wenig Information über die Verlässlichkeit ihrer Schätzungen. Da diese Informationen Entscheidungen zur Anpassung an das Risiko erleichtern, wird die Verlässlichkeit der Schadensschätzungen mit der neuen Methode dargestellt. Die Verlässlichkeit bezieht sich dabei nicht nur auf die Schadensschätzung selber, sondern auch auf die Annahmen, die über betroffene Gebäude gemacht werden. Nach diesem Prinzip kann auch die Verlässlichkeit von Annahmen über die Zukunft dargestellt werden, dies ist ein wesentlicher Aspekt für Prognosen. Die Darstellung der Verlässlichkeit und die erfolgreiche Anwendung zeigt das Potential der Methode zur Verwendung von Analysen für gegenwärtige und zukünftige hydro-meteorologische Gefahren.

Summary

Natural extreme events are an integral part of nature on planet earth. Usually these events are only considered hazardous to humans, in case they are exposed. In this case, however, natural hazards can have devastating impacts on human societies. Especially hydro-meteorological hazards have a high damage potential in form of e.g. riverine and pluvial floods, winter storms, hurricanes and tornadoes, which can occur all over the globe. Along with an increasingly warm climate also an increase in extreme weather which potentially triggers natural hazards can be expected. Yet, not only changing natural systems, but also changing societal systems contribute to an increasing risk associated with these hazards. These can comprise increasing exposure and possibly also increasing vulnerability to the impacts of natural events. Thus, appropriate risk management is required to adapt all parts of society to existing and upcoming risks at various spatial scales. One essential part of risk management is the risk assessment including the estimation of the economic impacts. However, reliable methods for the estimation of economic impacts due to hydro-meteorological hazards are still missing. Therefore, this thesis deals with the question of how the reliability of hazard damage estimates can be improved, represented and propagated across all spatial scales. This question is investigated using the specific example of economic impacts to companies as a result of riverine floods in Germany.

Flood damage models aim to describe the damage processes during a given flood event. In other words they describe the vulnerability of a specific object to a flood. The models can be based on empirical data sets collected after flood events. In this thesis tree-based models trained with survey data are used for the estimation of direct economic flood impacts on the objects. It is found that these machine learning models, in conjunction with increasing sizes of data sets used to derive the models, outperform state-of-the-art damage models. However, despite the performance improvements induced by using multiple variables and more data points, large prediction errors remain at the object level. The occurrence of the high errors was explained by a further investigation using distributions derived from tree-based models. The investigation showed that direct economic

impacts to individual objects cannot be modeled by a normal distribution. Yet, most state-of-the-art approaches assume a normal distribution and take mean values as point estimators. Subsequently, the predictions are unlikely values within the distributions resulting in high errors. At larger spatial scales more objects are considered for the damage estimation. This leads to a better fit of the damage estimates to a normal distribution. Consequently, also the performance of the point estimators get better, although large errors can still occur due to the variance of the normal distribution. It is recommended to use distributions instead of point estimates in order to represent the reliability of damage estimates.

In addition current approaches also mostly ignore the uncertainty associated with the characteristics of the hazard and the exposed objects. For a given flood event e.g. the estimation of the water level at a certain building is prone to uncertainties. Current approaches define exposed objects mostly by the use of land use data sets. These data sets often show inconsistencies, which introduce additional uncertainties. Furthermore, state-of-the-art approaches also imply problems of missing consistency when predicting the damage at different spatial scales. This is due to the use of different types of exposure data sets for model derivation and application. In order to face these issues a novel object-based method was developed in this thesis. The method enables a seamless estimation of hydro-meteorological hazard damage across spatial scales including uncertainty quantification. The application and validation of the method resulted in plausible estimations at all spatial scales without overestimating the uncertainty.

Mainly newly available data sets containing individual buildings make the application of the method possible as they allow for the identification of flood affected objects by overlaying the data sets with water masks. However, the identification of affected objects with two different water masks revealed huge differences in the number of identified objects. Thus, more effort is needed for their identification, since the number of objects affected determines the order of magnitude of the economic flood impacts to a large extent.

In general the method represents the uncertainties associated with the three components of risk namely hazard, exposure and vulnerability, in form of probability distributions. The object-based approach enables a consistent propagation of these uncertainties in space. Aside from the propagation of damage estimates and their uncertainties across spatial scales, a propagation between models estimating direct and indirect economic impacts was demonstrated. This enables the inclusion of uncertainties associated with the direct economic impacts within the estimation of the indirect economic impacts. Consequently, the modeling procedure facilitates the representation of the reliability of estimated total economic impacts. The representation of the estimates' reliability prevents reasoning based on a false certainty, which might be attributed to point estimates. Therefore, the developed approach facilitates a meaningful flood risk management and adaptation planning.

The successful post-event application and the representation of the uncertainties qualifies the method also for the use for future risk assessments. Thus, the developed method enables the representation of the assumptions made for the future risk assessments, which is crucial information for future risk management. This is an important step forward, since the representation of reliability associated with all components of risk is currently lacking in all state-of-the-art methods assessing future risk.

In conclusion, the use of object-based methods giving results in the form of distributions instead of point estimations is recommended. The improvement of the model performance by the means of multi-variable models and additional data points is possible, but small. Uncertainties associated with all components of damage estimation should be included and represented within the results. Furthermore, the findings of the thesis suggest that, at larger scales, the influence of the uncertainty associated with the vulnerability is smaller than those associated with the hazard and exposure. This leads to the conclusion that for an increased reliability of flood damage estimations and risk assessments, the improvement and active inclusion of hazard and exposure, including their uncertainties, is needed in addition to the improvements of the models describing the vulnerability of the objects.

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Abbreviations

CART	Classification and Regression Tree
CIT	Conditional Inference Tree
CGE	Computable General Equilibrium
EO	Earth Observation
GDP	Gross Domestic Product
IO	Input Output
MAE	Mean Absolute Error
MBE	Mean Bias Error
OSM	Open Street Map
OOB	Out of Bag
RF	Random Forest
RMSE	Root Mean Squared Error
SAB	Saxon Relief Bank
SDF	Stage Damage Function

1 Introduction

1.1 Motivation

Natural hazards have always been a threat that humans have to deal with. Over the course of time and evolution, the preparedness of human communities towards natural hazards has grown. However, with the progressive development of societies, also the amount of valuable objects exposed to the hazards has increased. In addition, the dynamic natural systems and the interaction of anthropogenic and natural systems have changed and continue to change the boundary conditions.

Hydrological events, such as river or coastal floods can affect large areas. However, hydrological events are not per se considered as natural hazards or even as natural disasters. The interplay between anthropogenic and natural components is needed to turn a natural event into a hazard. As soon as humans are severely negatively affected, e.g. by damaged properties or even fatalities, a natural event can be determined as a natural disaster. Records of large flood events even data back several thousand years (Baker, 1987). The research field of Paleo-hydrology identifies flood events that took place 10.000 years ago based on sediments deposited in the tributary mouths (Kochel & Baker, 1982). However, in the aftermath it is not clear whether these events had a disastrous impact on humans.

The first records of damage to societies caused by hydrological hazards go back to the second century before Christ (Börngen, 2011). Since then many more devastating riverine or coastal floods have been recorded (Börngen, 2011; Weikinn, 1958; Deutsch *et al.*, 2010) and surely the number of unrecorded cases of all event sizes around the world is even higher. Devastating events such as the coastal floods first and second "grote Mandränke" in the years 1362 and 1634 at the North Sea coast caused approximately up to 100.000 fatalities (Börngen, 2011; Sager, 1972). In the year 2016, hydro-meteorological hazards, such as tropical storms and floods, claimed approximately 6.900 human lives and caused a financial loss of about 110 billion US Dollars globally (MunichRE, 2017). These numbers illustrate that the impacts of these events have potentially always had tremendous consequences for societies.

However, humanity is not only a victim. Manipulations of natural systems e.g. in form of land transformations (Vitousek *et al.*, 1997), lead to the development of complex coupled human and natural systems, which might react in nonlinear and unforeseeable ways (Liu *et al.*, 2007). Climate change can be considered as one of the consequences provoking i.a. extreme weather and therefore potentially natural hazards (IPCC, 2012). Although the consequences of climate change have been recognizable across all natural systems for several years (Parmesan & Yohe, 2003), the manipulations are still ongoing and getting in part even worse (Martin *et al.*, 2016).

In recent years, with faster changing natural and societal systems, the question on the impacts of hydrological hazards became more and more urgent. Many models show an increasing number of flood events coming along with a warmer climate in many parts of the world (Alfieri *et al.*, 2017; Hirabayashi *et al.*, 2013), requiring an urgent adaptation to these changing conditions (Willner *et al.*, 2018a). A recent study also revealed a shift in European flood timing due to a changing climate (Blöschl *et al.*, 2017). This might lead to the need of adjusted flood management strategies in Europe.

However, not only the natural systems are under change but also the societal systems and hence the exposure to hydrological hazards changes. The world population is constantly increasing (United Nations Population Division, 2017), which fosters the development of mega cities (Taubenböck *et al.*, 2012). This leads to an increase in urban patterns which are exposed to hydrological hazards (Gueneralp *et al.*, 2015). Overall, anthropogenic and natural systems are undergoing change and therefore constant adjustments of the management in view of uncertainties is needed. These adjustments must also be implemented across spatial scales.

One important part of these management strategies is the quantification of risk associated with a hydrological hazard. This quantification requires knowledge about the hazard itself, the exposed elements and their vulnerability towards the hazard. However, methods for an appropriate estimation of the impacts of the events are still inaccurate (Meyer *et al.*, 2013), since these components usually suffer from high uncertainties. These inaccuracies are so far not represented within the estimations and can therefore not be communicated appropriately (Kreibich *et al.*, 2014; Ward *et al.*, 2015). In addition, these unrepresented uncertainties may give a false sense of certainty in estimations leading to questionable conclusions from projection studies. Consequently, there is a need for accurate flood risk assessments, which communicate their reliability at any spatial scale, enabling a meaningful adaptation to future flood events as well as the analysis of past flood events.

1.2 Present status of flood risk assessments

The definition of risk can be summarized as the likelihood over a period time that a certain hazard negatively affects parts of the society, which are exposed to this hazard (IPCC, 2012). Consequently, risk can be described as a product of a hazard, the exposed elements and their vulnerability towards the hazard (Kron, 2005).

The analysis of past flood events and the assessment of future flood risk is an important part of flood risk management. Flood damage assessments are an integral part of flood risk management. The models used for these assessments estimate the damage which could potentially be caused by a flood event. Flood damage assessments also comprise i.a. the three components hazard, exposure and vulnerability. Flood risk management and damage assessments take place at different spatial scales, i.e. the level of a single building, up to a city, countries or even continents.

In this thesis, flood damage models should be looked at from three different perspectives. The first is the model as a description of the damage processes. The second is the estimation at different spatial scales. The third is the handling of uncertainties that are associated with the assessments.

Damage processes

The role that flood damage models play in risk and damage assessments is the description of the vulnerability of a certain object to a flood event. In other words, the models aim to predict how much damage an object with specific characteristics would suffer, in case it is hit by a flood. The characteristics of the flood can be expressed e.g. by the water level at the object. Usually it is differentiated between direct and indirect damage. Direct damage is generally caused by physical contact of flood water with e.g. buildings, while indirect damage can occur both spatially and temporally independently of the flood event (Merz *et al.*, 2010). An example is the indirect economic impact on companies outside the flooded area affected due to disruptions in the supply chain.

There is a variety of models aiming to describe the flood damage processes. A so-called stage-damage-function (SDF) relates the water level at a building to the direct damage caused by the flood (Grigg & Helweg, 1975). The SDF is a single-variable model, since the damage caused is only driven by one single variable, which is mainly the water level (Meyer *et al.*, 2013). Due to its simplicity the SDF is still the most widely used damage model (Scawthorn *et al.*, 2006; Smith, 1994; Emschergenossenschaft & Hydrotec, 2004; MURL, 2000). In contrast, multi-variable models make use of more than one variable to improve the models and make more reliable predictions. During the last years a broad range of applications and multi-variable models using many variables were investigated including: multi-coloured manual (Penning-Rowsell *et al.*, 2005), FLEMO (Thieken *et al.*, 2008; Kreibich *et al.*, 2010), tree-based models (Merz *et al.*, 2013; Hasanzadeh Nafari *et al.*, 2016c; Wagenaar *et al.*, 2017), bayesian networks (Schröter *et al.*, 2014; Vogel *et al.*, 2014), regression models (Poussin *et al.*, 2015).

These models consider variables such as the water level, contamination of the water, the building material, early warning and many more. Some studies aim to identify these damage-influencing variables to improve the understanding of the damage process and therefore the performance of the models (Zhai *et al.*, 2005; Hudson *et al.*, 2014; Merz *et al.*, 2013; Thieken *et al.*, 2005). However, the predictions of most of the models are still quite inaccurate indicating a need to find additional ways to improve the damage estimations (Meyer *et al.*, 2013). This is especially true for the damage estimations of companies, since most of these studies are dealing with the improvement of models describing the damage to private households (Gerl *et al.*, 2016). Companies are less studied, mainly because the data is more heterogeneous and scarce than the data for private households (Gissing & Blong, 2004). At the same time, the damage suffered by companies is an important part of the total economic impact of flood events and thus also an essential part of flood risk assessments. Consequently, an improvement of the performance of models describing the flood damage processes, especially of models predicting flood damage to companies, would contribute to an increasing reliability of flood risk assessments.

Uncertainty

Uncertainty is a term mentioned in almost any study on flood risk, yet the uncertainty is rarely assessed and quantified in a comprehensive way (Merz *et al.*, 2010), despite the fact that risk assessments should always be accompanied by an uncertainty analysis (Apel *et al.*, 2008). Uncertainties are associated with each of the components of risk assessments and damage estimations, namely hazard, exposure and vulnerability (Table 1.1).

The hazard for damage assessments after flood events is typically described by a water mask delineating the flooded areas. Water masks can usually provide variables like the water level and eventually the timing and duration of the flood event. For (future) risk assessments also flood frequencies, precipitation and runoff generation (Apel *et al.*, 2004) play an important role in addition to the corresponding water masks. These variables can be affected by uncertainties cascading through meteorological, hydrological and hydraulic models (Pappenberger *et al.*, 2005). One way to represent this uncertainty is to make use of different models estimating the respective variables (Apel *et al.*, 2009; Altarejos-García *et al.*, 2012).

Table 1.1: Overview of uncertainties associated with flood damage estimations, their typical representations and exemplary studies.

Component	Description	Typical representations	Exemplary studies
Hazard	uncertainty regarding the modeling of the hazard intensities	include results of different models or distributions	Apel *et al.* (2009) Hirabayashi *et al.* (2013)
Exposure	uncertainty regarding the exposed elements (number, characteristics, asset values)	use of different land use data sets or scenarios	de Moel & Aerts (2011) Winsemius *et al.* (2016)
Vulnerability	uncertainty regarding the damage estimation of a single object	comparison of the results of different flood damage models	Cammerer *et al.* (2013) Wagenaar *et al.* (2016)

For global projection studies of flood risk, ensembles of projections are used to provide a range of water masks (Hirabayashi *et al.*, 2013).

The description of the exposure depends strongly on the spatial scale at which the assessment takes place. It can range from the use of single buildings (Huttenlau *et al.*, 2010), to land use data sets at the municipal or country level (Kreibich *et al.*, 2016) or to the use of the gross domestic product (GDP) at the country or continent level (Ward *et al.*, 2013). In any of these applications, the exposed elements, their characteristics and asset values are uncertain. In most cases, land use data is used, often in conjunction with an asset value disaggregation (Seifert *et al.*, 2010b). Uncertainties associated with the characteristics and asset values are mostly not quantified or represented in post-event studies. Some studies make use of different land use data sets to assess the uncertainty (de Moel & Aerts, 2011). For the assessment of future risk, the consideration of different socio-economic scenarios (Jongman *et al.*, 2015; Winsemius *et al.*, 2016) can mimic the uncertainty of the future development of exposed elements.

The description of vulnerability is uncertain in terms of damage processes, which cannot be described appropriately. This mainly originates from shortcomings of the methods, a lack of data, as well as from a lack of understanding of the damage processes (Meyer *et al.*, 2013). Many studies address this uncertainty by taking results of different models into account (Wagenaar *et al.*, 2016; Cammerer *et al.*, 2013). The consideration of several models may show the uncertainties associated with model setup and parameter estimation, but it does not describe the uncertainties associated with the actual damage process. Egorova *et al.* (2008) introduced beta distributions in which mean values are located on a SDF to include the uncertainty of the damage process also within the results. However, apart from this study, the uncertainty of a single model is mostly not included within the results.

In the present status of flood risk assessments a comprehensive quantification and representation of the uncertainty associated with the hazard, exposure and vulnerability is not conducted. Most studies only address the uncertainty of one component. Moreover, studies that aim to link models for different types of damage, e.g. models predicting the direct and indirect economic impacts of a flood event, also miss quantifying and propagating the uncertainty associated with the estimation of the direct economic impacts (Carrera *et al.*, 2015; Jonkman *et al.*, 2008; Koks *et al.*, 2015). A representation would facilitate the communication of the reliability of damage estimates (Hall & Solomatine, 2008). Furthermore, reliable future projections should reflect all uncertainties associated with their estimations and assumptions to prevent a false certainty in the results and consequently misleading conclusions.

Spatial scales

In general flood risk assessments and damage estimations can take place at any spatial scale (de Moel *et al.*, 2015). Usually one distinguishes between the micro-, meso- and macro-scale. The micro-scale is the smallest spatial scale and usually covers single buildings up to small parts of a city. Meso-scale assessments usually range from the municipality to the federal state level. The macro-scale contains large areas at the size of countries. Some studies also distinguish the supra-scale, which then comprises continents or even the entire globe.

The approaches and data sets used differ between the various spatial scales. The methods which are usually used, as e.g. SDF or tree-based models, are mostly derived at the object level. However, these models are then applied at larger spatial scales to different exposure data sets, such as land use data (Kreibich *et al.*, 2016) or GDP (Ward *et al.*, 2013). Consequently, this leads to methodological inconsistencies (Schwierz *et al.*, 2010). Further inconsistencies may arise from the exposure data sets themselves. For example, the density of objects and therefore asset values might vary strongly in a specific area, which cannot be detected in land use data (Jongman *et al.*, 2012a). Hence, inconsistencies within the data sets and the applied methods lead to a reduced reliability of the modeling results.

Furthermore, a link between spatial scales has not been established yet (de Moel *et al.*, 2015). This inhibits, firstly, a consistent down- or upscaling of risk assessment and secondly the propagation of uncertainties between the spatial scales. Especially for the purpose of adaptation, reliable risk information across all spatial scales is necessary (Adger *et al.*, 2005). Therefore, a consistent representation and propagation of risk information as well as damage estimation and the associated uncertainties across spatial scales would increase the reliability of risk assessments.

1.3 Objectives and Structure

The analysis of past flood events and the projection of future flood risk requires a reliable flood damage estimation across all spatial scales. Current methods are not able to describe the damage process accurately and are similarly unable to represent and propagate uncertainties appropriately. Hence, the overarching research objective of this thesis is the investigation of the reliability of flood damage estimations. Specifically, the description of damage processes at the object-level, the consistent handling of spatial scales and the representation of uncertainties in model results and their propagation between spatial scales and different models should be investigated. The research is carried out using the example of companies in Germany. The **overarching research question** is the following:

> How can the reliability of hazard damage estimations and risk assessments be improved, represented and propagated consistently across spatial scales?

This thesis comprises three main Chapters in the form of manuscripts to facilitate the answering of this question. The three Chapters are arranged in a structure oriented along the spatial scales (Figure 1.1). Each of them aims to answer a specific part of this question, even though the answers given to one part of the question may also contribute to the answer of another part of the question. Consequently, Chapter 2 and 3 contribute to the improvement of the description of damage processes for an increasing reliability of damage estimates. Chapter 3 introduces a novel method for seamless damage estimation across spatial scales including a representation of the reliability. Chapter 3 and 4 contribute to the propagation of this reliability between models and between spatial scales up to the national level.

In more detail, Chapter 2 assesses micro-scale tree-based models to increase the understanding of damage processes by identifying damage-influencing variables at the object level and to assess the model performance with regard to the quantity of the data sets. Hence, the first study builds micro-scale tree-based models for the estimation of flood damage to companies, which are also used in the two successive studies.

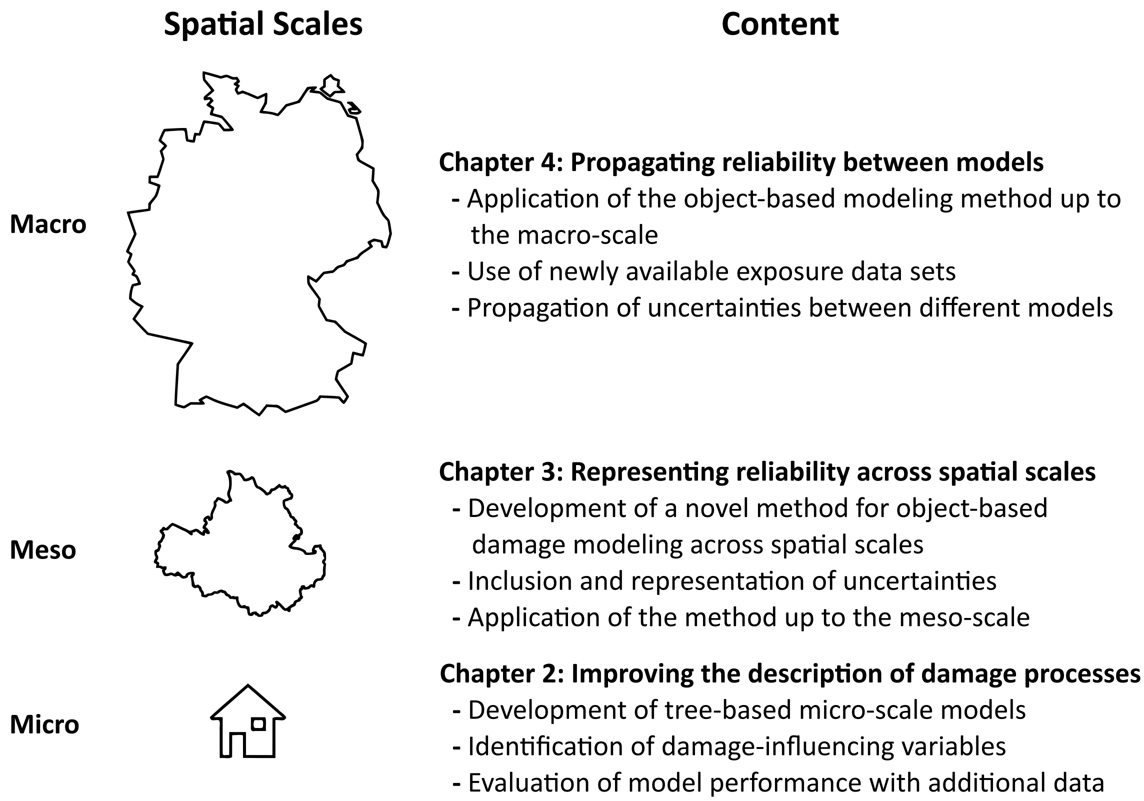

Figure 1.1: *Bottom-up structure of the thesis along spatial scales.*

The second study deals with the representation of the reliability of damage estimates and the propagation along spatial scales. For this purpose, Chapter 3 develops, applies and validates a novel method that enables the inclusion of uncertainties associated with the damage estimations within the model results and allows for a seamless spatial scaling. The application and validation takes companies into account and covers the micro to the meso-scale.

The third study develops a modeling procedure, which enables the propagation of uncertainties between models estimating the direct economic impacts and models estimating the indirect economic impacts. Hence, Chapter 4 applies the method, developed in Chapter 3 to companies, up to the national level based on newly available exposure data sets, and propagates the uncertainties between different models.

1.4 Author Contributions

The main part of this thesis consists of three manuscripts, which have been published, or are submitted and are intended to be published in international peer-reviewed journals. Most of the work presented in the manuscripts has been performed by the author. However, all co-authors on the manuscripts listed in the respective chapter contributed to work with comments, ideas and discussions as well as reviewing the manuscripts. Author contributions of the three manuscripts are as follows:

Chapter 2: Conceptualization: T.S., K.V., H.K., B.M.; Formal Analysis: T.S.; Investigation: T.S., K.V.; Methodology: T.S., K.V.; Visualization: T.S., K.V.; Software: T.S.; Supervision: H.K., B.M.; Writing - Original Draft: T.S.; Writing - review & editing: T.S., K.V., B.M., H.K..

Chapter 3: Conceptualization: T.S., K.V.; Formal Analysis: T.S.; Investigation: T.S., K.V.; Methodology: T.S., K.V.; Visualization: T.S.; Software: T.S.; Supervision: H.K., B.M.; Writing - Original Draft: T.S.; Writing - review & editing: T.S., K.V., B.M., H.K..

Chapter 4: Conceptualization: T.S., H.K., R.M.; Formal Analysis: T.S.; Investigation: T.S.; Methodology: T.S., K.V., T.Sc.; Visualization: T.S.; Software: T.S.; Supervision: H.K., B.M., R.M.; Writing - Original Draft: T.S.; Writing - review & editing: T.S., K.V., T.Sc., B.M., H.K..

In addition to the above mentioned manuscripts, the author also participated in the following publications, which are not included in the thesis:

Laudan, J., Rözer, V., **Sieg, T.**, Vogel, K. & A. H. Thieken 2017. Damage assessment in Braunsbach 2016: Data collection and analysis for an improved understanding of damaging processes during flash floods. *Natural Hazards and Earth System Sciences*, **17**(12), 2163–2179.

Kuhlicke, C., Masson, T., Kienzler, S., **Sieg, T.**, Thieken, A. H. & H. Kreibich. 2018. Multiple flood experience and social resilience: Findings from three surveys on households and companies exposed to the 2013 flood in Germany. *Weather, Climate and Society*. ***submitted***

Schmitt, A., **Sieg, T.**, Wurm, M. & H. Taubenböck. 2018. Investigation on the separability of slums by multi-aspect TerraSAR-X dual-co-polarized high resolution spotlight images based on the multi-scale evaluation of local distributions. *International Journal of Applied Earth Observation and Geoinformation*, **64**, 181–198.

Sultana, Z., **Sieg, T.**, Kellermann, P., Müller, M. & H. Kreibich. 2018. Assessment of business interruption of flood-affected companies using Random Forests. *Water.*, **10**(8).

Vogel, K., Özturk, U., Riemer, A., Laudan, J., **Sieg, T.**, Wendi, D., Agarwal, A., Rözer, V., Korup, O. & A. H. Thieken. 2017. Die Sturzflut von Braunsbach am 29. Mai 2016 - Entstehung, Ablauf und Schäden eines "Jahrhundertereignisses". Teil 2: Geomorphologische Prozesse und Schadensanalyse. *Hydrologie und Wasserbewirtschaftung*, **56**(3), 126–134.

Vogel, K., Laudan, J., **Sieg, T.**, Rözer, V., Winter, B. & A. H. Thieken. 2017. Data collection for a damage assessment after the flash flood in Braunsbach (Germany) in May 2016. *GFZ Data Services*.

2 Tree-based flood damage modeling of companies: damage processes and model performance

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Published as:
Sieg T., Vogel K.,
Merz B., Kreibich H.
Tree-based flood damage modeling of companies: Damage processes and model performance.
Water Resources Research.
2017;53:1-19.
doi:10.1002/2017WR020784.

Abstract

Reliable flood risk analyses, including the estimation of damage, are an important prerequisite for efficient risk management. However, not much is known about flood damage processes affecting companies. Thus, we conduct a flood damage assessment of companies in Germany with regard to two aspects. Firstly, we identify relevant damage-influencing variables. Secondly, we assess the prediction performance of the developed damage models with respect to the gain by using an increasing amount of training data and a sector-specific evaluation of the data. Random Forests are trained with data from two post-event surveys after flood events occurring in the years 2002 and 2013. For a sector-specific consideration, the data set is split into four subsets corresponding to the manufacturing, commercial, financial, and service sectors. Further, separate models are derived for three different company assets: buildings, equipment, and goods and stock. Calculated variable importance values reveal different variable sets relevant for the damage estimation, indicating significant differences in the damage process for various company sectors and assets. With an increasing number of data used to build the models, prediction errors decrease. Yet, the effect is rather small and seems to saturate for a data set size of several hundred observations. In contrast, the prediction improvement achieved by a sector-specific consideration is more distinct, especially for damage to equipment and goods and stock. Consequently, sector-specific data acquisition and a consideration of sector-specific company characteristics in future flood damage assessments is expected to improve the model performance more than a mere increase in data.

2.1 Introduction

Extreme flood events like the riverine flood of 2013 in Europe have severe and manifold impacts on society, including huge financial damage to the economy (Merz *et al.*, 2014; Schröter *et al.*, 2015; Thieken *et al.*, 2016). The total tangible damage caused in Germany in 2013 is estimated at 6.67 billion Euros, of which 1.48 billion Euros was suffered by private households and 1.32 billion Euros was suffered by the business sector (Bundesministerium des Innern, 2013). Their share of about one-fifth of the total damage reveals companies' large damage potential. Yet, damage processes particularly in the business sector are not very well understood and are consequently difficult to model, resulting in an urgent need to gain more knowledge on flood damage accrued to companies (Meyer *et al.*, 2013; Bubeck & Kreibich, 2011). Many different factors, such as e.g. the water level, the placement of equipment or goods and the preparedness of the company, can affect the process leading to flood damage (Kreibich *et al.*, 2007).

Since flood risk analyses, including damage modeling, are an essential prerequisite for efficient flood risk management, the identification and quantification of the damage driving factors is highly important. Flood risk analyses are carried out at different spatial scales including the supra-national (global), macro- (national), meso- (regional) and micro-scales (local) (de Moel *et al.*, 2015). Many studies assessing flood risk on the micro- to meso-scale model the damage in monetary terms on the basis of factors such as e.g. water depth, the contamination of the water or the land use of a certain area (Apel *et al.*, 2009; Falter *et al.*, 2015; Gerl *et al.*, 2014; Huttenlau *et al.*, 2010; Kim *et al.*, 2012; Koks *et al.*, 2014b). Some studies assessing flood risk, expressed as, e.g., the affected amount of the gross-domestic product and population, on the meso- to macro-scale include factors such as demography indices or other socio-economic indicators to model the impacts of flood events (Koks *et al.*, 2014a; Ward *et al.*, 2013; Winsemius *et al.*, 2013). More and more authors claim that societies' vulnerability must be taken into account in flood risk assessments in order to enable a more precise estimate of flood risk and identify effective adaptation measures (Mechler & Bouwer, 2014; Jongman *et al.*, 2015). Commonly, the most detailed data is available at the micro-scale, enabling an in-depth assessment of the damage processes. Thus, improving the understanding of what influences damage and vulnerability on the micro-scale can support flood risk assessments on all spatial scales.

So far, several methods were used to determine flood damage-influencing factors to achieve a more precise description of the damage processes. Zhai *et al.* (2005), for instance, used a logistic and a multivariate regression model to estimate the flood damage to residential buildings and their contents, as well as to determine its influencing factors for the Tokai flood in Japan of 2000. Yet, some factors that were considered important for the damage process, such as flood preparedness, were not taken into account for damage modeling due to their non-linear effects (Zhai *et al.*, 2005). Hudson *et al.* (2014) aimed at identifying effective flood damage mitigation measures for private households by means of propensity score matching. One drawback of this method is the need for relatively large sample sizes to get reliable estimates for the effectiveness of the measures. Merz *et al.* (2013), for instance, applied bagging decision trees and regression trees to quantify the importance of various factors for the amount of damage and to model the flood damage to residential buildings.

In general, flood damage models use important damage-influencing variables as input to estimate the damage of elements at risk. Most models consider the type or use of the building or property and the water level as most important factors determining the damage (Scawthorn *et al.*, 2006; Smith, 1994; Emschergenossenschaft & Hydrotec, 2004; MURL, 2000). This concept goes back to the observation of Grigg & Helweg (1975) "that houses of one type had similar depth-damage curves regardless of actual value". Other models include additional factors to describe these processes, including precautionary measures, contamination, building quality, etc. (Hasanzadeh Nafari *et al.*, 2016a; Penning-Rowsell *et al.*, 2005; Thieken *et al.*, 2008). Recent studies used machine learning, multi-variable and multivariate approaches to assess flood damage (Kreibich *et al.*, 2016; Merz *et al.*, 2013; Hasanzadeh Nafari *et al.*, 2016c; Poussin *et al.*, 2015; Schröter *et al.*, 2014; Vogel *et al.*, 2012). Schröter *et al.* (2014) and Merz *et al.* (2013) claimed that tree-based models, such as Random Forests (Breiman, 2001), are suitable for flood damage modeling as they are able to capture non-linear and even non-monotonous dependencies between predictor and response variables and they take interactions between the predictors into account. Furthermore, they are able to identify the relevant predictor variables from the set of all considered variables and can be trained from data sets of various sizes, since intrinsic regularization criteria control the complexity of the derived model based on the available training data. However, while most of these studies cover damage to private households, flood damage to companies and its drivers are rarely assessed.

Regarding the flood damage estimation of companies, various models for different company sectors have already been suggested by previous studies. For instance, one of the first and very comprehensive approaches has been the Blue Manual of Penning-Rowsell & Chatterton (1977) which contains stage-damage curves for both residential and commercial property in the UK. In one of its successors, the multicoloured manual, Penning-Rowsell *et al.* (2005) distinguished between the following four classes of non-residential properties: retail, warehouse, office and factory. Different stage-damage-functions per business sector are provided in HAZUS-MH (Scawthorn *et al.*, 2006). The multi-variable flood damage models FLEMOcs (Seifert *et al.*, 2010a) and FLFAcs (Hasanzadeh Nafari *et al.*, 2016b) distinguish between different business sectors within the models.

However, to our knowledge, a sector-specific assessment of damage driving variables and estimation of flood damage to companies by means of machine learning has not yet been conducted. This may be due to a lack of suitable data sets, since this is particularly limiting data-driven flood damage assessments of companies (Merz *et al.*, 2010; Meyer *et al.*, 2013; Molinari *et al.*, 2014). The amount of available data is much smaller than for private households and the heterogeneity within the data is much greater due to the large variety of companies (Kreibich *et al.*, 2005; Merz *et al.*, 2010). The questions of how much data is needed to build a reliable model and what can be gained from using more data have rarely been discussed so far. An exception based on private households is for instance the study by Schröter *et al.* (2016).

The objective of this study is a flood damage assessment of companies from different sectors on the micro-scale with respect to two aspects. The first aspect is the identification of damage-influencing variables to improve the understanding of the flood damage processes of companies. The second aspect is the analysis of the flood damage model performance with respect to increasing data set sizes. Both aspects should lead to a better idea of (1.) what and (2.) how much data is necessary to describe and quantify damage processes of companies. We propose the Random Forest (RF) approach as a powerful tool to identify relevant predictor variables with linear and non-linear dependencies from limited data. A meaningful feature selection not only improves the understanding of the damage process, but also enables the development of suggestions for an improved data acquisition, which can then focus on the important damage determining variables.

2.2 Data & Methods

In the following, Random Forests are trained on post-event survey data to identify important predictor variables for the estimation of flood damage caused to different company assets: (a) buildings, (b) equipment, and (c) goods and stock. Within this context, a sector-specific consideration is realized by splitting the data into four subsets, following Kreibich *et al.* (2007), each representing one of the four considered sector types: (1) manufacturing, (2) commercial, (3) financial, and (4) service. RFs are trained for each combination of sector type and company asset, as well as for the complete (sector-unspecific) data set. The prediction quality for the developed sector-specific and unspecific damage models is evaluated via cross-validation depending on the size of the training data set used. The derived models, and consequently, the identified predictors and the prediction quality depend strongly on the data used for training. To provide representative results, the construction of the RFs is repeated several times, with different data subsets sampled from the entire data set. Figure 2.1 illustrates the entire work-flow of this study.

The following section 2.2.1 describes the survey data set used. The concept of RFs is explained in section 2.2.2, while section 2.2.3 describes the sampling scheme used for repeated model construction. The measures applied for the validation of the flood damage models are outlined in section 2.2.4.

2.2.1 Survey data

The data sets used are taken from two surveys conducted after the floods in the Elbe and Danube catchments in the years 2002 and 2013 in Germany (Kreibich *et al.*, 2005, 2007; Thieken *et al.*, 2016). The surveys were carried out by the SOKO Institute by means of computer-aided telephone interviews in October 2003, May 2004 and between May and July 2014. In total, 479 interviews were conducted for the flood in 2002 and 557 for the flood in 2013, whereby the interviewed companies were chosen from a site-specific random sample based on lists of affected streets in the corresponding areas (Kreibich *et al.*, 2005). The surveys of the 2002 and 2013 floods were conducted in a similar, comparable way. Questions about the following topics were asked in the surveys: flood impact parameters (e.g. contamination, water level), early warning, emergency measures, precautionary measures, company characteristics, flood damage and flood experience. The person with the best knowledge about the flood damage was questioned for each company (Kreibich *et al.*, 2005). Given answers were cross-checked during the interview to improve the data quality and to clarify contradictory answers. See Kreibich *et al.* (2005, 2007) and Thieken *et al.* (n.d.) for further details about the

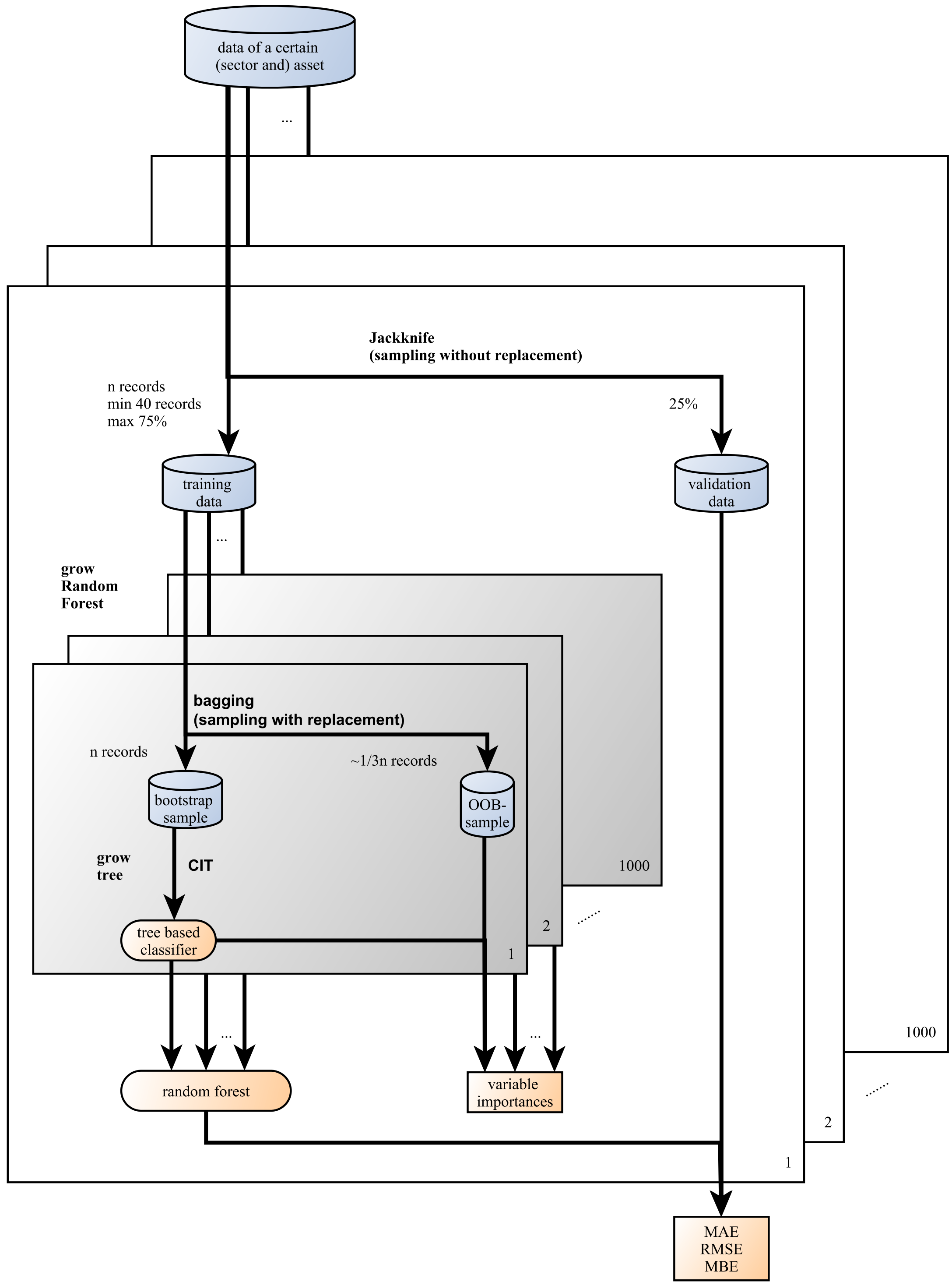

Figure 2.1: Flowchart of the sampling schemes used in this study.

survey and the data processing.

Table 2.1 shows the nine variables used in this study as potential flood damage predictors, which were derived from the data set. The variables were selected according to data availability and their potential to influence company flood damage according to previous studies (Penning-Rowsell *et al.*, 2005; Scawthorn *et al.*, 2006; Kreibich *et al.*, 2007, 2010). Variables describing the impact of the flood are the water level, the inundation duration and the contamination indicator, as used in other studies on damage modeling for companies by Kreibich *et al.* (2010) and Seifert *et al.* (2010a). The contamination indicator is the weighted sum of different contaminants such as oil, sewage water or chemical substances, whereas contaminants which are expected to have a higher damaging potential are weighted accordingly (Büchele *et al.*, 2006). Variables characterizing companies' resistance to flooding are the adaptation ratio, the mitigation ratio and the emergency indicator. The adaptation and mitigation ratios correspond to the fraction of implemented measures compared to all measures relevant for damage reduction. For example, the installation of flood-proof oil tanks is only relevant for companies, that have oil tanks on their premises. Information about the relevance of the respective measures was requested in the survey, i.e. the companies were asked for each measure, if this measure is relevant for their company. A one was added to both numbers to avoid zeros in the fraction.

$$ratio = \frac{measures_{undertaken} + 1}{measures_{relevant} + 1} \tag{2.1}$$

Hence, a ratio of 1 indicates that all relevant measures were implemented.

Table 2.2 gives an overview of all measures obtained by the survey and their classification as adaptation, mitigation or emergency measures. Measures are classified as adaptation measures if the use or location of an asset/object is changed, that is, if an area is used in a different way or dangerous substances are relocated from areas which are prone to flooding. Measures are classified as mitigation measures if the use of an asset/object remains, but is protected in a certain way. An example of this would be the use of flood-proof oil tanks in flood-prone areas. The emergency indicator is the sum of the number emergency measures adopted, whereby eight different measures were named in the surveys and are therefore counted. However, the emergency indicator varies between zero and four, since the maximum number of emergency measures undertaken by a company was four measures. Variables describing the companies' characteristics are the number of employees and the spatial conditions of the company, indicating whether a company owns premises with more than one building or less than one floor in an externally used building. It can be assumed that the damage processes are different for businesses in a shopping street that own only a few rooms than

***Table 2.1:** Variables used in the models (C: continuous; O: ordinal).*

	Predictor Variable	Abbreviation	Values (Scale and Range)
Flood impact			
	Water level	wst	C: 0 cm to 960 cm above ground
	Inundation duration	d	C: 0 to 1440 h
	Contamination indicator	con	O: 0 = no contamination to 6 = heavy contamination (7 classes)
Damage reduction			
	Adaptation ratio	adapt	O: 0.25 = low adaptation to 1 = high adaptation (6 classes)
	Mitigation ratio	mitig	O: 0.16 = low mitigation to 1 = high mitigation (11 classes)
	Emergency indicator	emerg	O: 0 to 4 emergency measures undertaken (5 classes)
Company			
	Size	size	C: 1 to 800 employees
	Spatial situation	spatial	O: 1 = business premises with more than one building 2 = one entire building used by the company 3 = at least one floor in an externally used building 4 = less than one floor in an externally used building
	Response Variable		
Damage			
	Relative damage of buildings	rloss	C: 0 to 1 damage ratio
	Relative damage of equipment	rloss	C: 0 to 1 damage ratio
	Relative damage of goods & stock	rloss	C: 0 to 1 damage ratio

for companies, that own entire premises. The relative loss (rloss) is calculated as the recorded asset damage divided by the recorded asset value. Damage ratios were calculated for three types of assets: (1) buildings, (2) equipment and (3) goods and stock. The damage ratio could not be calculated for each record, since not every interviewee answered the question on the respective asset damage and/or asset value. Records with missing values for either asset damage or asset value were discarded for the respective asset. The resulting data set used for the analysis does not contain any missing values. If companies declared that

Table 2.2: *Precautionary measures and their classification*

Classification	Measure
Adaptation	
	adapted use of the flood-prone area
	relocation of susceptible equipment
	relocation of dangerous substances
Mitigation	
	flood-proof oil tanks
	flood-proof silos
	flood-proof air conditioning
	stable building foundation, waterproof-sealed cellar, etc.
	water barriers
Emergency	
	emergency plan
	number of emergency exercises
	installation of water barriers
	installation of water pumps
	installation of emergency power
	saving equipment and goods
	preventing contamination
	switching off machines, power etc.

certain assets were not damaged by the flood, the corresponding rloss values were assumed to be zero. Around 11 % of the interviewed companies declared damage to all three asset types.

The analysis was undertaken separately for companies from different sectors. Companies were divided into four sectors following NACE Rev. 2 (Nomenclature statistique des Activites economiques dans la Communaute Europenne) according to the European statistical classification of economic activities in the European Community (Eurostat, 2008): the manufacturing sector (Mining and Quarrying, Manufacturing, Electricity, Gas, Steam, and Air Conditioning Supply, Water Supply; Sewerage, Waste Management and Remediation Activities, Construction; NACE classes B-F), the commercial sector (Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles, Transportation and Storage, Accommodation and Food Service Activities; NACE classes G-I), the financial sector (Information and Communication, Financial and Insurance Activities, Real Estate Activities, Professional, Scientific and Technical Activities, Administrative and Support Service Activities ; NACE classes J-N), and the service sector (Public Administration and Defence; Compulsory Social Security, Education, Human Health and Social Work Activities, Arts, Entertainment and Recreation, other Service Activities ; NACE classes O-S).

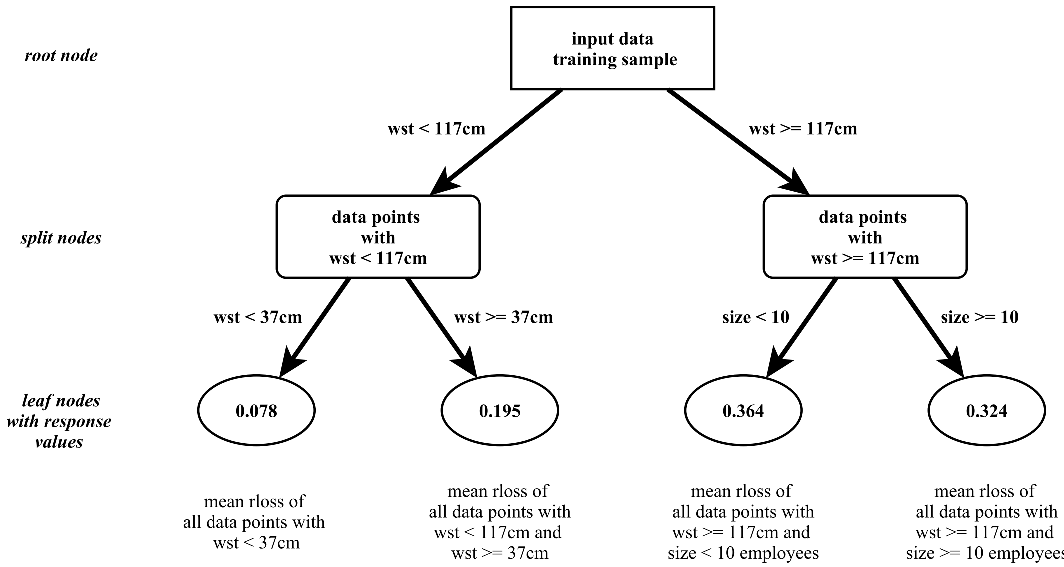

Figure 2.2: *Exemplary representation of a single tree of a Random Forest for visualizing and explaining the approach. The tree consists of one root node, two split nodes and four leaf nodes.*

2.2.2 Random Forests

In this study, RFs are used to identify important damage-influencing variables by means of the variable importance and to model the flood damage. A RF is an ensemble of n tree-based classifiers, whereby every tree is grown from a randomly sampled subset of the input data set. Tree-based models are suitable for flood damage modeling, as they allow for nonlinearities, predictor interactions and the use of categorical and continuous variables (Merz *et al.*, 2013; Schröter *et al.*, 2014; Kreibich *et al.*, 2016). In the following, we give a basic insight into tree-based classifiers and RFs. For a detailed introduction we refer to Breiman (2001).

Figure 2.2 shows an exemplary tree to support the following introduction of RFs. The input training data sample corresponds to the root node of a single tree and is split recursively (branching) into subsamples that form the nodes of the tree. Each split is guided by a threshold value of a predictor, which is chosen such that the resulting subsamples minimize the heterogeneity of the response variable. The final subsamples form the leaf nodes, from which the response value is derived (Figure 2.2). For the prediction of the response variable of a certain data point the values of the predictor variables determine the leaf node that needs to be considered. For a categorical response variable (classification tree) the response value corresponds to the most frequent class of the leaf node’s subsample. In case of a continuous response variable (regression tree), the mean value of the leaf node's subsample is returned (Figure 2.2). The predicted response value of a RF is derived from the response values of the single classification or regression trees, by taking the mode or the mean value, respectively. As we use RFs with continuous response variables, from now on we will mainly focus on the aspects which are relevant for regression trees.

RFs apply a bootstrap sampling called bagging internally to define the training subsamples of the single trees. Only about two-thirds of the data sample is used to build a single tree, while one-third of the sampled data subset is left out. The data points, which are not taken into account for the training of the classifier are called Out-of-Bag observations (OOB). The OOB observations are used internally to calculate quality measures of the resulting model and to estimate the variable importance.

The literature provides different algorithms, such as the Classification And Regression Tree (CART) algorithm, THAID, C4.5 (Quinlan, 1986) and the Conditional Inference Tree (CIT) algorithm (Hothorn *et al.*, 2006) to build the individual trees (Wei *et al.*, 2015). One of the most popular and widely used algorithms is CART. However, many studies have observed a bias in the CART algorithm with respect to variable selection towards variables with different scales and many possible splits (Kass, 1980; Segal, 1988; White & Liu, 1994; Jensen & Cohen, 2000; Shih, 2004; Strobl *et al.*, 2007), which affects the interpretability of the models (Hothorn *et al.*, 2006). The CIT algorithm was developed to reduce this bias.

The main differences between CART and CIT are the methods used to select and split variables (splitting criterion) and to identify leaf nodes (stop criterion). CART uses an exhaustive search method on a randomly chosen set of m variables to identify the variable with the best split based on a measure of node impurity. The node impurity is usually measured as the mean square error MSE of the response values in the respective parts. The splitting is stopped either if a certain threshold of node impurity is reached or if no further splitting is possible. The OOB observations are used for an internal cross-validation, which intends to avoid overfitting. CIT makes use of hypothesis tests to identify the splitting variable at each node, whereby the dependence between the variables and the response is assessed by multiple procedure tests. At each node a randomly chosen set of variables can be used as candidate variables for splitting. The variable with the strongest association, measured by the p-value of the hypothesis test, to the response variable is selected as the splitting variable. If no association between the response variable and the covariates in the current node can be stated this node is defined as a leaf node. Hothorn *et al.* (2006) showed structural differences between the models resulting from the two algorithms, while reaching similar prediction accuracies. In addition, trees grown with the CIT algorithm are less prone to the problem of overfitting, since the variable selection and the stopping of the tree growth is done by appropriate statistical testing (Hothorn *et al.*, 2006). The algorithm CIT allows for an unbiased variable selection for variables with different scales and many possible splits, which improves the interpretability of the trees.

To our knowledge, previous studies that used regression trees for the estimation of flood damage made use of the CART algorithm (Merz *et al.*, 2013; Schröter *et al.*, 2014; Hasanzadeh Nafari *et al.*, 2016c). However, since the data sets used contain variables with different scales as well as many possible splits, and since an unbiased variable selection is key for the identification of damage-influencing variables, the algorithm used in this study is CIT. The analysis was done with R (version 3.3.2) - a language and environment for statistical computing (R Core Team, 2017). The package "party" (version 1.2) was used to compute the RFs (Hothorn *et al.*, 2015). Each RF consists of 1000 trees (ntree = 1000) and 3 variables were randomly chosen as candidate variables at each node for splitting (mtry = 3). Each terminal node consists of at least 7 observations.

Variable importance

Apart from modeling applications, RFs can also be used to identify relevant predictor variables from a set of input predictor variables. The relevance can be assessed by the so-called variable importance. In the case of regression, this importance can be estimated by a random permutation of the values of the corresponding predictor variable, simulating the absence of this particular variable. The difference of the prediction error calculated by means of the OOB observations with and without the permutation indicates whether or not the predictor variable is important for the prediction. The rationale behind this is that the prediction accuracy will decrease if a relevant predictor variable is permuted randomly. Therefore, the increase of the prediction error with the permutation of the corresponding predictor variable can be interpreted as a measure for the variable importance.

2.2.3 Sampling of the data sets

Due to the large heterogeneity of the data, the learned RF and its predictions depend on the respective data sample used for training. In addition to the sampling which takes place within the RFs, a further data sampling is applied before the training of the models to provide stable and comparable results. Hence, many RFs are trained with different data samples and the averaged results are provided in section 2.3. The results shown in section 2.3 are therefore an outcome of many differently trained RFs.

The sampling method used is the Jackknife, which was developed to assess the stability of estimates (Rodgers, 1999). To assess the effect of the data set size on the model performance, the size of the samples is increased step-wise by one data point until a maximum of 75% of the respective data set is reached. The data points are sampled without replacement from the original data set. The 25% of the data set which is not used for the sample is used for the validation of the RF, trained with this particular sample. For the calculation of the variable importance measures 75% of the data points of the respective data sets are used. The data sets are sampled 1000 times per asset, sector and data size step. Hence, 1000 RFs are built per asset, sector and data size step.

2.2.4 Flood damage model performance

RFs trained with data from only one sector (sector-specific) and those trained with data from all sectors (sector-unspecific) are built and compared with each other. A leave-p-out cross-validation is performed to evaluate the results of the RFs. The validation of the predicted relative damage is done with 25% of the respective data set, which was not used for the training of the model. Three measures are used to evaluate the performance of the models:

the mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|est - obs| \tag{2.2}$$

the root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(est - obs)^2} \tag{2.3}$$

the mean bias error (MBE)

$$MBE = \frac{1}{n}\sum_{i=1}^{n} est - obs \tag{2.4}$$

The MAE describes the average deviation from the predicted to the observed values, while the RMSE considers the square of the errors. Compared to the MAE, the RMSE is more strongly affected by large deviations. In the ongoing discussion on the choice of MAE or RMSE (Willmott & Matsuura, 2005; Willmott *et al.*, 2009), Chai & Draxler (2014) suggest considering both metrics in the model validation. In addition, the MBE describes a systematic overestimation or underestimation of the model.

2.3 Results & Discussion

The following section contains the analysis of the data and the results of the RFs. Section 2.3.1 provides a descriptive analysis and a short discussion of the data sets used. The results of the RFs regarding the identification of damage-influencing variables are given in section 2.3.2, while the performance of the models is analyzed in section 2.3.3. Both sections are subdivided into the three different assets (buildings, equipment, goods and stock) and followed by a discussion on the general findings.

2.3.1 Descriptive analysis of the data sets

Figure 2.3 shows the distribution of the variables represented by violin plots and the number of points available per asset and sector. The distribution of the variables were estimated by means of Kernel Density Estimator. For this overview, all variables were scaled from 0 to 1. Only a few companies from the financial and service sectors have goods and stock. Therefore, the case numbers are very small. Nonetheless, these few case numbers are analyzed and shown, but the results should be considered with caution.

The values of the relative damage vary not only between the sectors, but also between the assets. Manufacturing companies show the highest mean value for relative building damage, while commercial companies show the highest mean value for relative equipment damage. Compared to the distributions of the relative building damage, distributions of the equipment as well as the goods and stock damage show a higher number of cases in which the entirety of the equipment or goods and stock of a company was damaged. The distributions of the water level and the inundation duration are relatively similar across all sectors and assets. For all assets, the mean values for the contamination index of manufacturing and commercial companies are slightly higher than the mean values of financial and service companies. Most companies were only marginally affected by contamination, as the contamination indices are low in general. The distributions of the mitigation ratio indicate that most companies did not undertake all the mitigation measures that they considered to be relevant. There are only slight differences between the sectors and assets. However, the distributions of the adaptation ratio reveal that many companies undertook all adaptation measures that they considered to be relevant. This can on the one hand be explained by the fact that the implementation of adaptation measures, such as changing the use of flood-prone areas within the business premises, demands less effort than most mitigation measures, such as retrofit building to make them flood-proof. On the other hand, some adaptation measures are rather specific, e.g. the relocation of

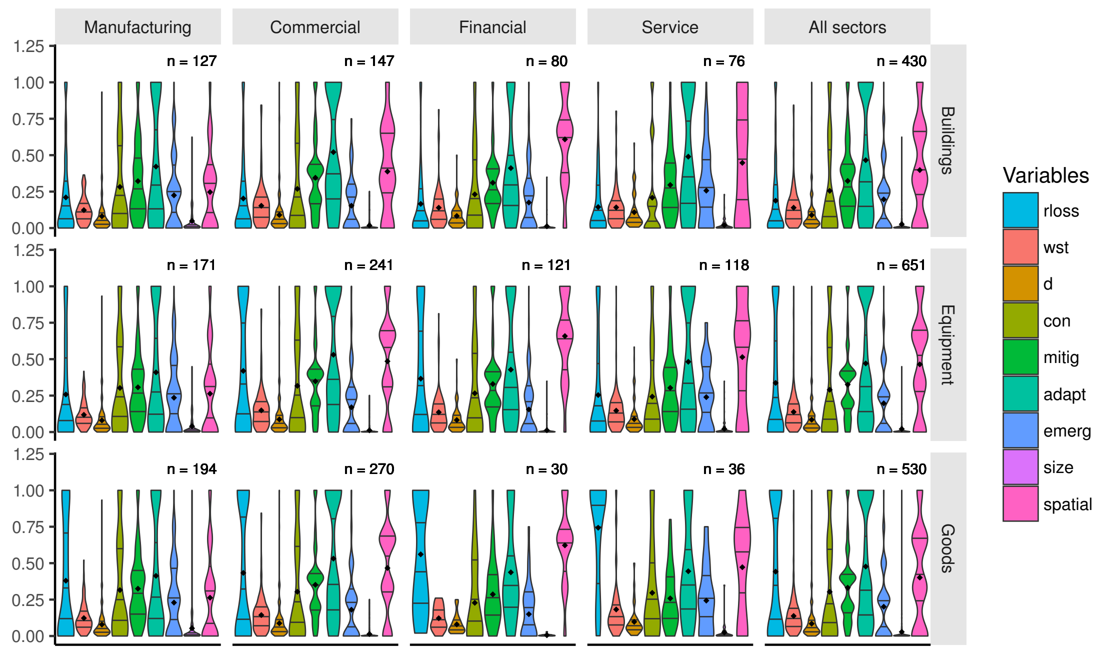

Figure 2.3: *Kernel density estimations of the nine variables for all assets and sectors based on the available data sets. Variables are scaled from zero to one. The lines represent the first, second and third quartiles. The dot represents the mean.*

hazardous substances, and are therefore not relevant for all of the companies. The number of the emergency measures taken is slightly higher for manufacturing and service companies. The same can be observed for the number of employees. The distributions of the spatial situation show clear differences between the sectors. Manufacturing companies mainly own one or more buildings, while financial companies have mostly one floor or less. This is plausible, as most manufacturing companies have more employees and need space for storage and production sites.

Figure 2.4 shows the correlation matrices of the nine variables per asset and sector. The used correlation coefficient is Spearman's rank correlation coefficient. The first column of each matrix contains the correlation coefficients of the relative loss and the predictor variables. In general, correlation coefficients range from 0.48 to -0.50, whereas most of the correlations are around 0. Water level, inundation duration and contamination have the highest positive correlation with the relative damage for all sectors and assets. The highest negative and significant correlations with relative damage has the variable adaptation ratio. Other variables significantly negatively correlated with relative damage are the mitigation ratio, emergency measures and spatial situation.

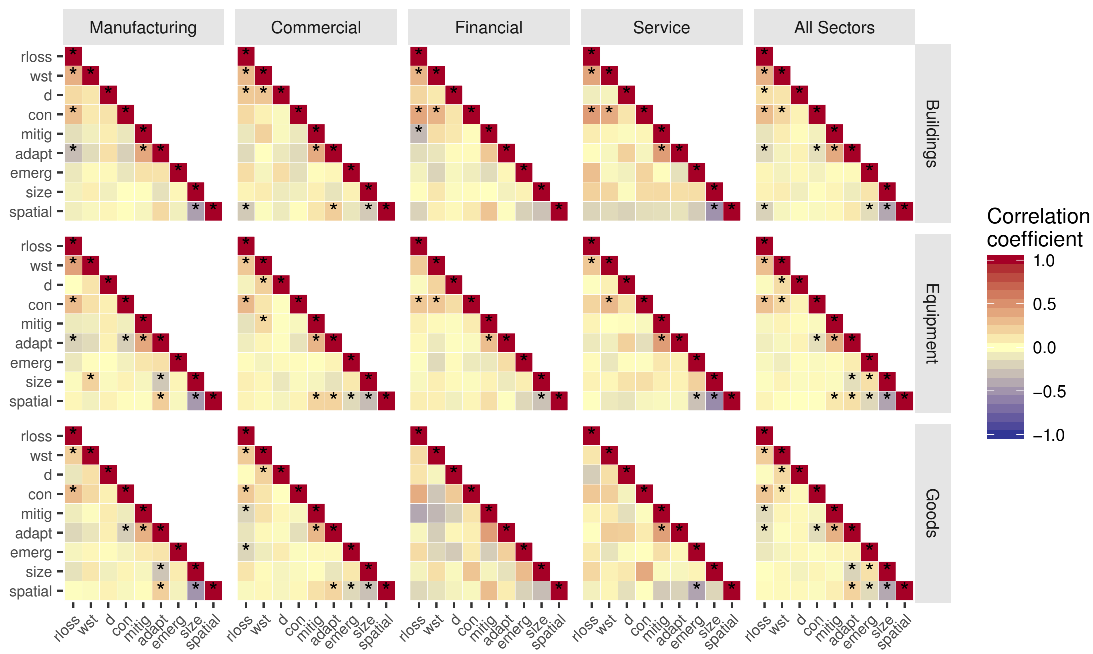

Figure 2.4: *Pairwise Spearman correlation coefficient for the nine variables. Stars show significant correlation at the 1% significance level.*

The predictor variables are also correlated with each other. Since the data considered for the different assets are subsets of the same data set - sampled according to the available damage information of the respective asset - the correlations between the predictors show similar patterns over all assets of the same sector. Yet, due to different sample sizes, significant correlations are partly missing especially for smaller subsamples (e.g. subsets considering the building damage and the financial or service sectors). For instance, in the manufacturing sector the significant negative correlation between adaptation ratio and contamination is not detected in the buildings subset, as well as the pairwise correlations between size, spatial situation and adaptation ratio. The correlation matrix is used to support the interpretation of the variable importances in section 2.3.2.

However, the correlation coefficients consider only pairwise and monotonic relationships. RFs are able to capture non-monotonic and multi-variable relationships, since they consider dependencies between the predictors as well. Therefore, influences of variables which cannot be detected by correlation coefficients might be detected by the variable importance measures of RFs.

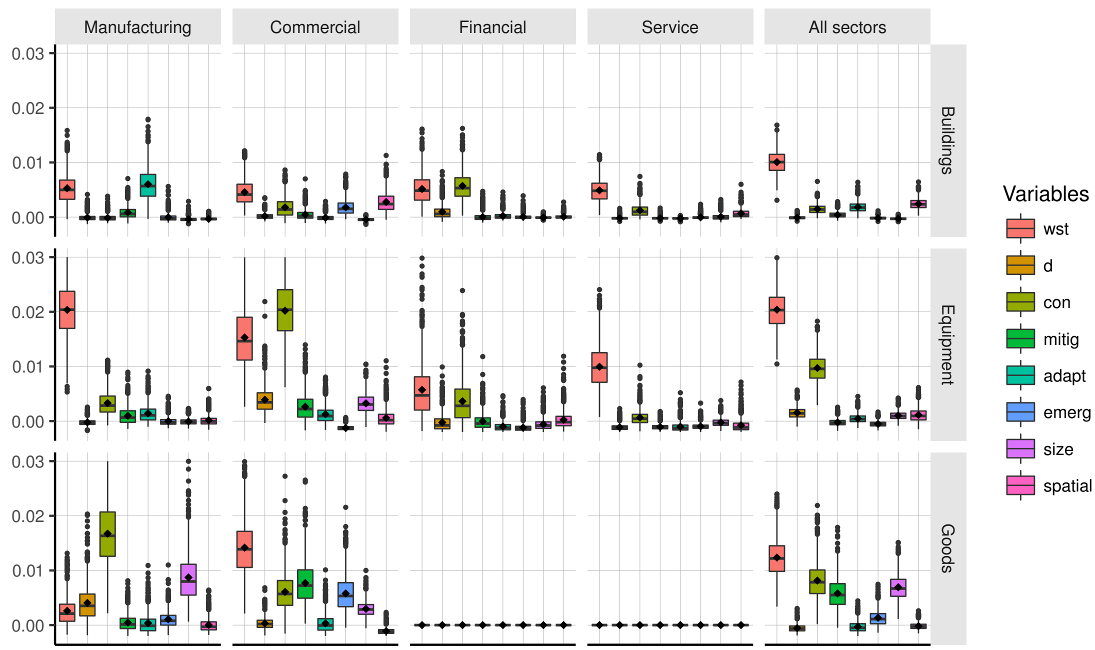

Figure 2.5: *Variable importances derived by 1000 Random Forests trained with individually sampled data sets. The variable importance is measured by the increase of the mean squared error (MSE) with the random permutation of the respective variable. The lines in the individual boxes indicate the quartiles, while the diamond indicates the mean value of the respective variable. The number of available data points was not sufficient to estimate the variable importances for goods and stock from the financial and service sectors.*

2.3.2 Variable importances

Figure 2.5 shows boxplots of variable importances of the eight predictor variables for different company sectors or all sectors together and different assets derived from RFs.

Buildings

The most important predictor variable for RFs predicting rloss of buildings is the water level, when considering companies from all sectors. This is consistent with many studies and existing models (Gerl *et al.*, 2014; Penning-Rowsell *et al.*, 2005; Hasanzadeh Nafari *et al.*, 2016b). However, the variable importance of the water level decreases in RFs trained with sector-specific data only. Furthermore, it can be observed that other variables apart from the water level influence the flood damage within the different sectors. Hence, certain influences can only be captured when distinguishing between the company sectors.

When predicting rloss of buildings from the manufacturing sector the variable adaptation ratio is slightly more important than the water level. This observation suggests that rloss is not only influenced by the water level, but also by the adaptation measures a company might have undertaken. Especially for manufacturing companies, adaptation measures such as the relocation of hazardous substances, could play an important role. This assumption is additionally supported by the negative correlation between rloss and the adaptation ratio (see Figure 2.4), indicating a damage-reducing effect of the above mentioned measures.

Important variables derived from RFs trained with company data from the commercial sector are the water level, spatial situation, emergency measures and contamination. The importance of the variable spatial situation in combination with the negative correlation with rloss leads to the assumption that the damage suffered by commercial companies depends to a certain extent on their business premises. This cannot be observed for companies from other sectors. One reason could be that the spatial situations in this sector are more heterogeneous, and consequently a good separation can be reached by this variable.

The variable importances from financial and service-oriented companies are dominated by water level and contamination. A stable separation based on other variables could not be found. This could on the one hand be an effect of the relatively low number of data points available for these company sectors. On the other hand, the predictors considered might not be sufficient for damage predictions, and hidden (not yet considered) variables are needed for an adequate damage description.

Equipment

Water level and contamination are identified as the most important variables when predicting rloss of equipment for companies from all sectors. In general, the range of the variable importances identified for equipment damage is larger compared to those for building damage. This indicates that the heterogeneity within the data and the processes describing the damage to equipment is larger than the heterogeneity within the building data.

Considering manufacturing companies only, the variable importance of the water level is high, while the importance of contamination is lower. Relatively high variable importances can be observed for the mitigation and adaptation ratios. Measures like the adjusted use of flood-prone areas at the company site could potentially lead to a decrease in the damage suffered by the companies’ equipment.

In addition, the adaptation ratio and contamination are negatively correlated with each other, indicating another damage-reducing effect of the adaptation measures, like the relocation of hazardous substances.

Companies from the commercial sector show high variable importances for water level and contamination, followed by inundation duration, mitigation ratio and size. While the Spearman correlation also identifies a significant correlation of water level and contamination with the damage caused (Figure 2.4), the significance threshold is not reached for the remaining predictors. The importance of inundation duration, mitigation ratio and size detected by the RF approach might be due to a non-monotonic relationship or - which we consider to be more likely - the impact on the relative loss becomes more obvious if multi-variable dependencies are taken into account. Thus, a pairwise correlation could be blurred by interfering factors (e.g. water level), but becomes more distinct for sorted data subsets that are formed in the tree growing process.

Variable importances for the financial and service sectors are lower in general and less diverse. Water level and contamination are identified as important variables for the financial sector, while the water level is the only important variable for the service sector. Similar to the results of the building damage, the lack of identified damage drivers is assumed to be due to the small sample sizes and/or hidden variables.

Goods and stock

RFs trained with data from all sectors to estimate the damage to goods and stock identify water level, contamination, mitigation ratio and size as the most important variables. This is the most diverse outcome compared to the other assets. Calculations of the variable importance of the damage to goods and stock for the financial and the service sectors were not possible due to the low number of data points.

The damage to goods and stock of manufacturing companies is mostly affected by contamination and the number of employees. Explaining the impact of company size is not straight-forward. It might not have a direct influence on the damage, but rather an indirect influence on several damage-driving and -preventing characteristics. Thus, Figure 2.4 reveals a correlation between company size and the spatial situation, as well as between company size and the adaptation ratio. Further, a slight, but not significant, positive correlation between size and water level is indicated considering the correlation matrix of goods and stock, which is even evaluated to be significant considering the correlation matrix of equipment. The correlation might be explained by location preferences of the companies depending on the size. Capturing information about several damage predictors, the company size might be preferred by the tree growing algorithm as a splitting criterion, rather than having split points for each of the correlated variables. Consequently, the correlated variables, such as water level, would be used less for data splitting, which explains their relative small variable importances.

The damage to goods and stock of companies from the commercial sector is mostly influenced by the water level. The degree of contamination has an influence as well, yet this effect is lower compared to the manufacturing companies. One reason for this could be that manufacturing companies are more likely to have hazardous material or liquids on their business premises which can potentially contaminate the water and consequently the other stocks. The emergency measures taken and the mitigation ratio show a relative high variable importance as well. Thus, a more efficient protection of goods and stock seems to be possible through emergency measures for companies from the commercial sector than from the manufacturing sector. This could be due to the characteristics of commercial companies' stock. The goods might be easier to relocate within a short time period than to rearrange the warehouse of a manufacturing company.

Discussion of the variable importances

In the previous subsections, the variable importance measure of RFs is used to identify relevant predictor variables for modeling companies' flood damage. Due to a limited data availability and heterogeneity in both company and flooding characteristics, general statements, despite the obvious impact of the water level, are hard to determine. Nevertheless, a distinction between different company sectors reduces the heterogeneity of the data and reveals sector-specific damage predictors not found in the joint consideration of all sectors. Thus, not only are new potential predictor variables for flood damage estimation recognized, but also different damaging processes are displayed for the different company sectors and assets. The provided variable importances give indications about the different damage processes, but the variance for some predictors is still large and possible conclusions should be considered carefully.

The robustness of the results might be increased for a larger data set that is less prone to deviations caused by outliers. Moreover, the heterogeneity within in the data could be decreased by further separations into smaller sub-sectors, which requires an increasing size of the total data set as well.

Furthermore, important variables describing damage processes seem to be missing (not recorded), especially for companies from the financial and service sectors. Many of the mitigation and adaptation measures included in this study are most likely not relevant for the damage processes of financial and service companies. An identification of these missing variables is hardly possible within the scope of this study, but a further differentiation of the company sectors during future data collections with a subsequent analysis could reveal additional factors that need to be considered.

Overall, the separation of the company sectors leads to a better insight into companies' flood damage processes. The benefit of considering different company sectors for prediction purposes as well as the effect of available training data is considered in the following section 2.3.3.

2.3.3 Flood damage model performance

This section presents and discusses the results of the validation of the RFs predicting flood damage separated by sectors. A validation of the models trained with the maximum number of available training data points is presented in Figure 2.6. In Figure 2.7 prediction errors of models built with different data set sizes are shown.

Model validation

Figure 2.6 shows boxplots of the three validation measures RMSE, MAE and MBE for sets of 1000 RFs predicting the damage to buildings, equipment and goods. RFs trained with data from only one sector (sector-specific) and trained with data from all sectors (sector-unspecific) are validated with independently sampled validation data sets and compared with each other. The validation is carried out with data from the same company sector that was used to train the model.

Buildings

The RMSEs of RFs trained with data from all company sectors have a mean value of approximately 0.25. Merz *et al.* (2013) estimated the building damage suffered by private households with bagging decision trees and regression trees. RMSEs around 0.1 were estimated, which is lower than the RMSEs estimated in this study. However, the data availability for private households is better than for companies, thus 1103 records were used to build the trees in Merz *et al.* (2013), while only 430 records were used in this study. This could lead to a better model performance. Furthermore, it can be assumed that the heterogeneity of the flood damage data for companies is higher than of the data for private households.

The mean value of the MAEs is approximately 0.18. These are lower errors compared to the validation results of the Flood Loss EstimationMOdel for the commercial sector (FLEMOcs) of Seifert *et al.* (2010a), who observed an MAE of 0.23. The results of the RFs seem to be more precise, although the applied

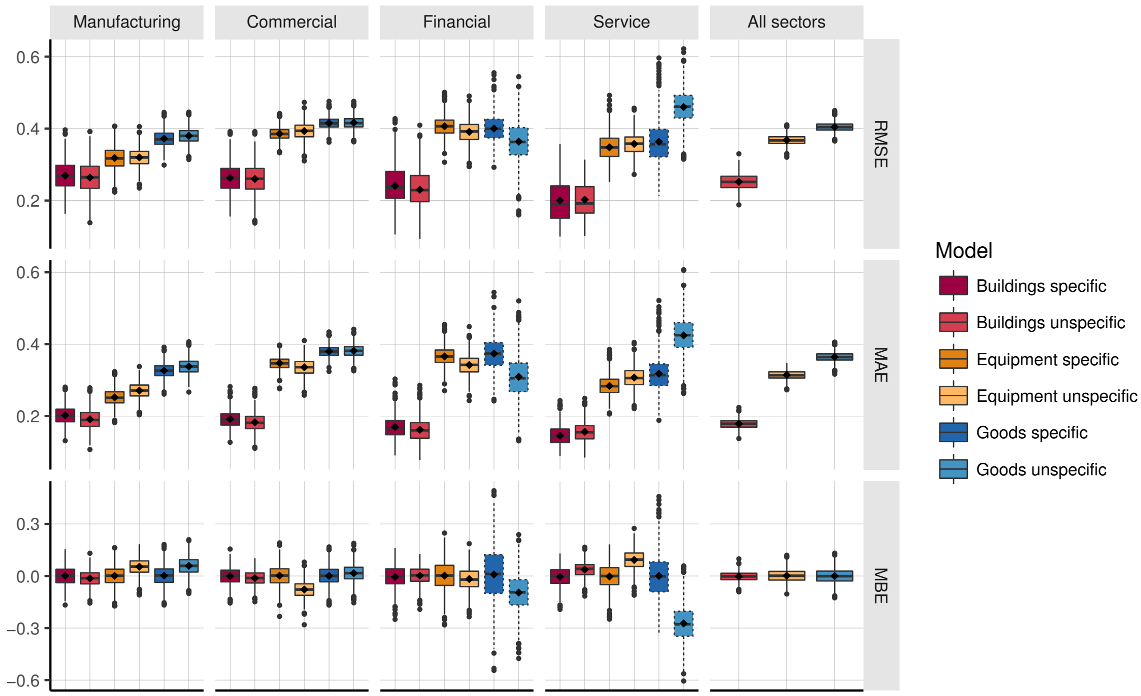

Figure 2.6: *Validation of flood damage to buildings (red), equipment (orange) and goods and stock (blue) estimated by 1000 individually trained Random Forests. Brighter colors indicate that the models were trained with sector-unspecific data. Measures used for validation are the root mean square error (RMSE, top), the mean absolute error (MAE, middle) and the mean bias error (MBE, bottom). Models trained with sector-specific data were trained with less data. Note that boxplots with dashed lines were generated with only a small data sample.*

validation methods are slightly different. The values of the MBE are around 0, which was also observed by Merz *et al.* (2013) and Seifert *et al.* (2010a).

The mean values of the results of the validation with data from the individual sectors are not much different from the validation with data from all sectors. Yet, the variation of the results is higher. This could mainly be due to the number of data points used for validation, which is lower for the validation of the individual sectors. Chai & Draxler (2014) noted that the robustness of the RMSE and MAE is lower, if only a few data points are available for the calculation of the measures. RFs trained with data points from individual sectors show similar values to those trained with data points from all sectors, when evaluated with samples from the respective company sector. Nevertheless, RFs built with data from all sectors were trained with more data.

The distributions of the MBE reveals that models trained with data from all sectors and models trained with data from a specific sector over- and underestimate the building damage in equal parts resulting in a mean MBE of around 0. Hence, there is no systematic over- or underestimation of the models for the manufacturing, commercial and financial sector. However, RFs trained with data from all sectors predicting damage to buildings from the service sector show a higher mean MBE than 0 indicating a systematic overestimation.

Equipment

The validation of RFs trained with data from all sectors shows a mean RMSE of 0.37 and a mean MAE of 0.31. The performance is similar to FLEMOcs, which was validated with a RMSE of 0.37 and a MAE of 0.30 (Seifert *et al.*, 2010a).

The validation results for all sectors and for each company sector differ more clearly. The MAE and RMSE values are higher for the commercial and financial sectors, while the values for the manufacturing and service sectors tend to be lower. This could partly be explained by higher variances and mean values for rloss in the commercial and financial sectors. RFs trained with data from one sector only perform slightly better than RFs built with data from all sectors, considering the manufacturing and service sectors. The opposite can be found when considering the commercial and financial sectors. The values of the MBE indicate a systematic overestimation of RFs trained with data from all sectors predicting the damage to equipment of manufacturing and service companies and a underestimation of the damage to equipment of commercial companies. The average estimations of models trained with data from single sectors are unbiased. Better results from RFs trained with data from one single sector support the assumption that different damage processes occur in the individual company sectors. However, particularly the model performance for the financial sector seems to profit more from additional data points than from sector-specific data.

Goods and stock

RFs trained with data from all sectors have mean values of 0.4 for RMSE and 0.37 for MAE. These errors are larger than those reported for the validation of goods and stock from FLEMOcs with a RMSE of 0.35 and MAE of 0.31 (Seifert *et al.*, 2010a). Thus, the performance of the RFs is lower compared to the estimation of rloss of goods and stock by FLEMOcs. The data sets used to derive the RFs are partly similar to those used for the derivation of FLEMOcs. FLEMOcs focuses on the event of 2002, while the RFs focus on both events from 2002 and 2013. Schröter *et al.* (2014) show that models trained with data from one event have a limited transferability to other events. This indicates event differences which are not captured within the models. Capturing two events leads to an increase in the data variability which might lead to higher validation errors.

RFs trained with data from one sector perform either equally well or slightly better than those trained with all sectors. In contrast, RFs trained with data from all sectors show a systematic overestimation when predicting the damage to goods and stock of manufacturing companies, while models predicting the damage to goods and stock of financial and service companies show a underestimation. This cannot be observed for models built with sector-specific data, leading to the conclusion that models built with sector-specific data should be preferred.

Effect of different training data sets

Figure 2.7 shows the mean values for RMSEs for RFs predicting the flood damage with a 95% confidence interval. Every point represents the mean RMSE of 1000 RFs, each built with an individually sampled training data set of size n. The size of the training data sets is stepwise increased to evaluate the effect of additional data points used for the training of the models. Although RFs can deal with large data sets, the method is also capable to provide reasonable results when trained with small data sets (Strobl *et al.*, 2007).

The smallest training data sets contain 40 data points, while the maximum is 75% of the size of the entire data set for the respective asset and sector (see Table 2.3 for the absolute numbers of data points). The RFs are divided into two groups: one was trained with data from one sector only (sector-specific RFs) and the other group was trained with data from all sectors (sector-unspecific RFs). The validation is always done with data sets from one sector only.

For almost all sectors and assets, a decrease in the mean RMSE with an increase of the training data set size can be observed. Table 2.3 compares the prediction performance of sector-specific and sector-unspecific models trained with the same amount of data (75 % of the sector-specific data), as well as sector-unspecific models trained with 75% of the entire asset-related data set. For each model considered, the percentages of the improvement in the RMSE compared to the worst performing model of the corresponding asset and sector are provided.

Considering the building damage, the distinction between sector-specific and sector-unspecific RFs hardly influences the model's prediction performance. Sector-specific RFs show a lower prediction error only in the service sector, while the errors in the other sectors are comparable. This results is plausible, since Figure 2.3 shows a similar distribution of the relative building damage over all sectors, which is in contrast to the large differences between the sectors for damage caused to equipment and goods. Further, it is reasonable that differences between the buildings of different companies are to a certain extend captured by

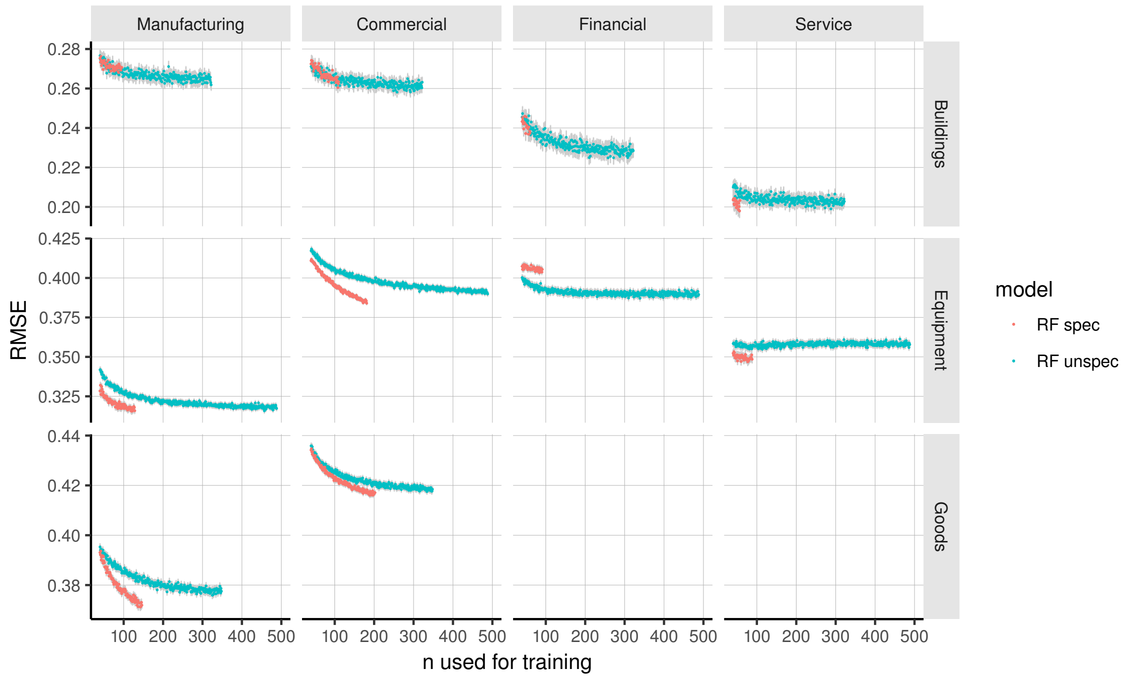

Figure 2.7: *Mean RMSE of sector specific (red) and sector unspecific (blue) Random Forests trained with differently sized data sets with a 95% confidence interval (light gray).*

the variable spatial situation, which receives the second highest importance in the RFs trained on all data. Hence, models trained with data from all sectors predict the building damage for any sector as precisely as models trained with data from the respective sector.

The mean prediction errors of sector-specific and sector-unspecific RFs estimating the equipment damage are significantly different from each other. Sector-specific models perform better than sector-unspecific models for the manufacturing, commercial and service sectors, when built with the same amount of training data points. This indicates that models trained with sector-specific data have a higher capability to model the damage accurately.

For the model performance analysis of RFs predicting damage to goods and stock, only companies from the manufacturing and commercial sectors were taken into account. The mean prediction errors of the sector-specific models are lower than those from the sector-unspecific models when trained with the same amount of data.

Table 2.3: *Performance improvement of RFs trained with sector-specific (spec) and unspecific (unspec) data sets. The improvement is shown as the relative decrease of the prediction error of RFs trained with all training data points available for the respective model compared to the highest prediction error of RFs predicting damage to the respective asset and sector. The columns "n spec" allow for a comparison between the performance of sector-specific and sector-unspecific models trained with the same amount of data points, whereas the columns "n total" present the improvement of sector-unspecific models trained with all available training data points.*

	Manufacturing		Commercial		Financial		Service	
	n spec	n total	n spec	n total	n spec	n total	n spec	n total
Buildings								
	n = 95	n = 322	n = 110	n = 322	n = 60	n = 322	n = 57	n = 322
spec	2.14 %	-	3.93 %	-	3.94 %	-	3.81 %	-
unspec	2.33 %	5.34 %	3.45 %	4.04 %	2.67 %	7.67 %	1.53 %	4.04 %
Equipment								
	n = 128	n = 488	n = 181	n = 488	n = 88	n = 488	n = 91	n = 488
spec	7.60 %	-	8.20 %	-	0.75 %	-	3.55 %	-
unspec	4.63 %	7.19 %	4.50 %	6.81 %	3.70 %	4.64 %	1.47 %	0.98 %
Goods & stock								
	n = 146	n = 348	n = 202	n = 348	-	-	-	-
spec	5.91 %	-	4.31 %	-	-	-	-	-
unspec	3.41 %	4.50 %	3.37 %	4.00 %	-	-	-	-

Discussion of the flood damage model performance

The validation of flood damage estimations by RFs shows reasonable results compared to other recently published models (Seifert *et al.*, 2010a; Merz *et al.*, 2013). Yet, the prediction errors are still relatively large, due to the high variation of damage values. Especially the damage to equipment of commercial companies as well as the damage to goods and stock of manufacturing and commercial companies follows a bimodal distribution, with the highest probabilities at the domain boundaries (Figure 2.3). A separation of both modes based on the predictors considered is only realized to a certain extent. Subsequently, the derived models that aim to minimize the mean squared error, provide estimates between the two peaks of the distribution, that differ more or less strongly from the observed values.

The variation in model performance is quite large and strongly depends on the data sampled for model training and validation. With respect to that high variation, the performance improvement of sector-specific compared to sector-unspecific RFs is rather small. Yet, the trend shows that models trained with specific data may outperform models trained with more, but unspecific, data.

The variation of the response variable that cannot be explained by the considered predictors indicates the existence of further predictor variables that have not been yet considered. Consequently, future flood damage studies should aim for the identification of as yet hidden damage-driving or -preventing factors, instead of merely increasing the amount of data. The observed improvement in sector-specific modeling suggests a stronger focus on variables that characterize individual companies and their assets. These variables could be e.g. information about the type of equipment, details about warehouses or specific characteristics about the companies' spatial situation. A further differentiation of the company sectors into subsectors could facilitate the specification. To support the higher model complexity that arises with additional predictors and to provide a representative data sample, an extended amount of data is suggested as well.

2.4 Conclusion

The objective of this paper was to study the flood damage caused to company buildings, equipment, and goods and stock with respect to two aspects. The first aspect is the identification of damage-influencing variables for company assets in general, as well as identifying different damage drivers for specific company sectors. The second aspect is the analysis of the flood damage model performance with respect to a sector-specific or unspecific consideration and with regard to the size of the available data set.

The most important variables identified are the water level, contamination, precautionary measures adopted, and the number of company employees. Differences between the sectors and assets can be found in terms of the identified important variables. For instance, adaptation measures taken are an important predictor variable for the building damage sustained by manufacturing companies, whereas the estimation of the building damage to commercial companies is influenced by the adopted emergency measures and the spatial situation of the company. These findings indicate that damage processes are different between the company sectors. The water level is identified as the most important variable. However, other variables are important as well, especially with regard to the damage to equipment and goods and stock. This supports the conclusion, drawn by other studies already, that water level is not sufficient to estimate the company damage caused by flooding.

For the analysis of the flood damage model performance, RFs trained with data from all sectors and those trained with data from only one sector were validated and compared with one another. Furthermore, the effect of different training data set sizes was investigated. Sector-specific models predicting damage to equipment and goods and stock mainly showed a lower prediction error when trained with the same amount of data points. Even with more training data, the performance of the sector-unspecific models was either equal to or lower than the performance of sector-specific models. Subsequently, models trained with more, but sector-unspecific, data do not necessarily result in more precise predictions. Future data collections should consequently focus on a sector-specific, detailed and reliable data acquisition to allow for a consideration of company-specific characteristics.

It can be concluded that the identification of damage drivers and processes remains difficult, not least because of the limited data. Yet, a sector-specific consideration reduces the heterogeneity in the data and helps to reveal new predictor variables. A sector-specific adaptation of damage models improves the prediction quality of the flood-related damage to all company assets considered.

3 Seamless estimation of hydro-meteorological risk across spatial scales

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Under review:
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Seamless estimation of
hydro-meteorological
risk across spatial scales.
Earth's Future.

Abstract

Hydro-meteorological hazards caused losses of approximately 110 billion US Dollars in 2016 worldwide. Current damage estimations do not consider the uncertainties in a comprehensive way, and they are not consistent between spatial scales. Aggregated land use data is used at larger spatial scales, although detailed exposure data at the object level is becoming increasingly available across the globe. We present a probabilistic approach for object-based damage estimation which represents uncertainties and is fully scalable in space. The approach is applied and validated to company damage from the flood of 2013 in Germany. Damage estimates are more accurate compared to models using land use data, and the estimation works reliably at all spatial scales. This method takes hydro-meteorological damage estimation and risk assessments to the next level, making damage estimates and their uncertainties fully scalable in space and enabling the exploitation of new exposure data.

Plain-Language Summary

The consequences of climate change have the potential to affect all of us. A warmer earth potentially triggers extreme weather events causing wind storms, droughts or floods, which can have severe impacts on society as a whole. Societies can reduce the impacts by being better prepared. This preparation can take place at the level of a single house, or a city, but also countries or even continents can prepare. In order to prepare, we need to know, in as much detail as possible, what impacts we have to prepare for and how severe these might get. Reliable guesses (estimations) of the consequences are required for each of these levels (house, city, country, continent). At present, the current methods do not communicate how reliable their estimations are. In addition, most of these methods estimate the consequences for only one specific level. In this study we present a new method which communicates the reliability of its estimations and works continuous across the various levels. Using the example of a flood that took place in Germany we show that the method works well at all levels and can therefore also be applied to estimate the impacts of events potentially happening in the future.

3.1 Introduction

In 2016 hydro-meteorological events caused more than 60 % of the overall losses due to natural hazards (MunichRE, 2017). The attribution of these hazards to climate change is still fuzzy and under debate (James *et al.*, 2014), yet the risk associated with hydro-meteorological hazards will most likely increase in the future (IPCC, 2012). Hence, the hazardous consequences of climate change require adaptation in all parts of society (IPCC, 2012; Moss *et al.*, 2012). However, informed decisions regarding natural hazard management are still heavily influenced by biases and uncertainty associated with damage estimates (Kreibich *et al.*, 2014). In fact, all components of the risk assessment, including the hazard, exposure and vulnerability, are affected by uncertainties. These uncertainties are not sufficiently represented in damage model results (Ward *et al.*, 2015).

Adaptation takes place at different spatial scales (Adger *et al.*, 2005). Consequently, hazard impact analysis and the associated uncertainties should be consistent across spatial scales. Yet, this spatial consistency remains challenging for the impact analysis of hydro-meteorological events (de Moel *et al.*, 2015; Prahl *et al.*, 2016) due to the use of different exposure data. Land use data, aggregated across (many) objects, is used for the large scale, whereas small-scale assessments are based on data at the object level (Jongman *et al.*, 2012a; Schwierz *et al.*, 2010).

Recently, however, exposure data sets at the object level have benefited from rapid technological improvements and an increase in data quantity and quality (Pittore *et al.*, 2017). Some of these projects, such as openbuildingmap.org or GED4GEM (Dell'Acqua *et al.*, 2013), were originally initiated to assess geophysical hazards, to provide specific information such as the occupancy or height of buildings at the object level. This kind of information could be used to assess damage caused to individual buildings by means of e.g. engineering-based hurricane damage models (Vickery *et al.*, 2006; Pita *et al.*, 2013) or multi-variable flood damage models (Merz *et al.*, 2013; Sieg *et al.*, 2017; Wagenaar *et al.*, 2017). So far, state-of-the-art damage models (Prahl *et al.*, 2016; Sieg *et al.*, 2017; Wagenaar *et al.*, 2017) are not able to keep up with this development causing a gap between what is currently done and what improvements would theoretically be feasible. Consequently, the value of this data has not been exploited for large-scale hydro-meteorological risk assessments.

3.2 The method of seamless estimation

We present a method for the seamless estimation of hydro-meteorological damage across spatial scales (Figure 3.1). It enables the exploitation of the newly available exposure data sets and provides consistency across scales, including a comprehensive uncertainty quantification. Damage estimates, which are provided as probability distributions for individual objects (e.g. buildings), are accumulated for an unrestricted and consistent spatial scaling. The method can be applied for pre-and post-event analysis.

This method uses the definition of risk as a product of the three components, hazard, exposure and vulnerability (Figure 3.1: A-C). Hazard can be described by variables like the water depth or wind speed taken from hazard maps, which can be modeled according to a chosen recurrence interval for pre-event analysis or based on observations for post-event analysis (Figure 3.1: A). Exposure is described by the number, kind and characteristics of exposed objects, which can be identified, for instance, by an overlap of hazard maps with building maps (Figure 3.1: B). Vulnerability is expressed by damage models describing the damaging processes affecting the individual objects. Any kind of hazard damage model (engineering- or empirically-based, single- or multi-parameter, etc.) can be used to describe the vulnerability of an exposed object and to estimate the damage (Figure 3.1: C).

Uncertainties are included by considering distributions instead of fixed values (Figure 3.1: D-E). Depending on the hazard damage model, information concerning the asset values and the damage-influencing variables is required. This includes the characteristics of the exposed objects (e.g. building type) or the extent to which the objects are affected by the hazard (e.g. water level or wind speed). These input variables of the damage models are prone to uncertainties, for instance, due to limited information as to the number and characteristics of the affected objects and the local hazard intensities. In cases where observations of the input variables are available, uncertainty associated with these observations can be included, e.g. by assuming a normal distributed error (Figure 3.1: D). If direct observations are unavailable, as is often the case, these variables can be treated as random variables, with their distributions based on expert knowledge or proxy data, e.g. official statistics, survey data or hazard maps (Figure 3.1: D). In both cases, these distributions represent the uncertainty of the hazard and exposure data. Several versions of exposed objects are then sampled from these distributions (Figure 3.1: D).

For each sampled object, the damage is estimated by applying the chosen damage model. Most damage models provide point estimates, that do not capture the uncertainties related to the damage process. For a consistent consideration of

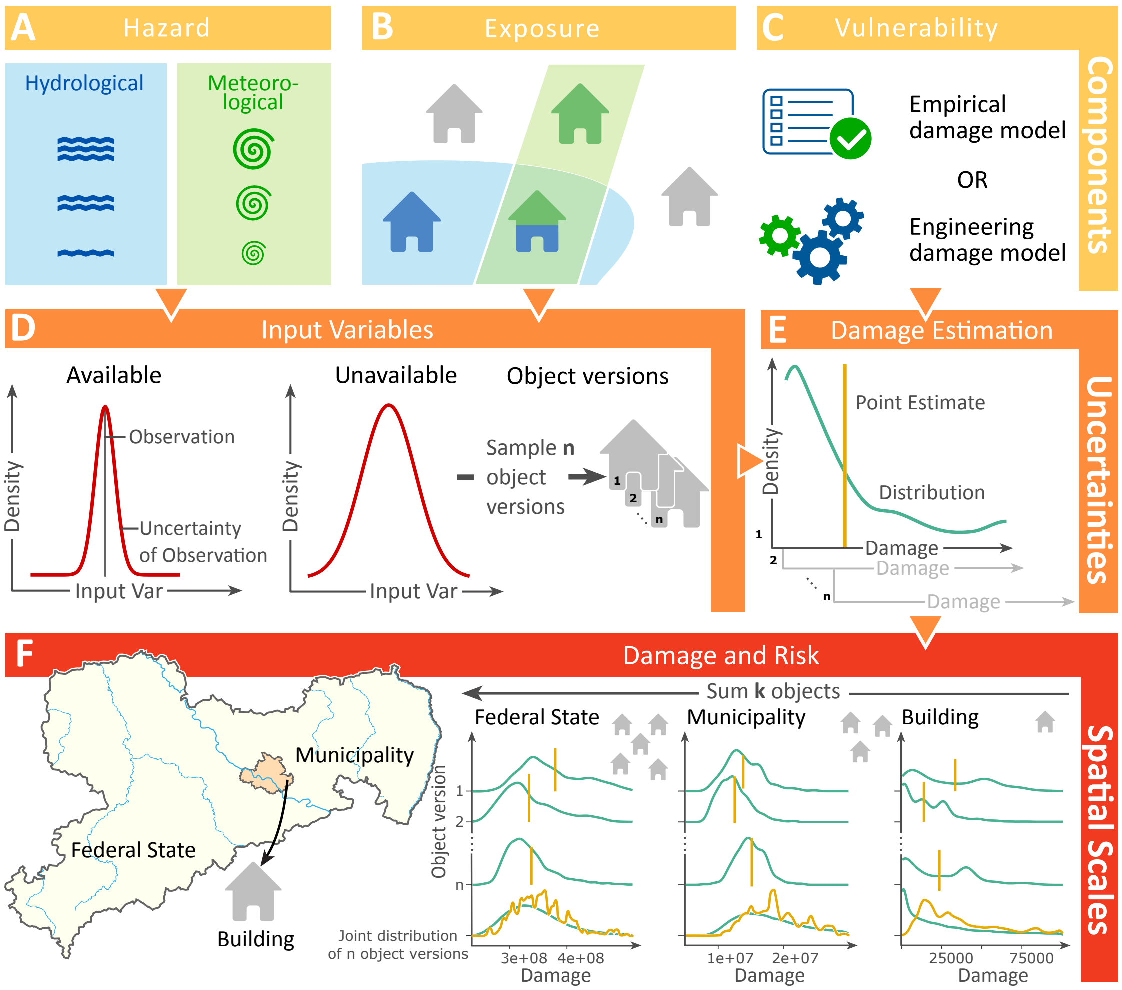

Figure 3.1: *The method includes the three components of hydro-meteorological risk: Hazard (A), Exposure (B) and Vulnerability (C). The consideration of associated uncertainties of input variables describing hazard and exposure (D) and the uncertainty within the damage estimation (E) by distributions. Application of seamless spatial scaling of damage estimations by summing up k affected objects (F).*

uncertainties, we suggest applying models that yield damage distributions instead (Figure 3.1: E), as it is done in a few studies, e.g. for the hazards of flooding (Egorova *et al.*, 2008), wind storms (Prahl *et al.*, 2015) or hurricanes (Wang *et al.*, 2017).

The combination of k objects in a specific area within the same sampling step n forms an object set. Summing up the damage estimates of individual objects within this object set enables seamless spatial scaling (Figure 3.1: F). Object sets can also be formed (and damage estimates summed up) according to other characteristics, e.g. objects that belong to a certain economic sector. Thus, the proposed method not only allows for consistent spatial scaling, but also for a detailed thematic grouping. Finally, the aggregation of n sampled object versions results in a probability distribution describing the possible damage under consideration of the uncertainties associated with the hazard, exposure and, depending on which damage model is used, the vulnerability.

3.3 Results & Discussion

We apply the method to the flood event occurring in central Europe in the year 2013 (Schröter *et al.*, 2015). The regional focus of the application is the federal state of Saxony, Germany. We simulated 300 object versions (Figure 3.1: D; $n = 300$) based on survey data and official statistical data from the German Federal Statistical Office (see supplementary materials for further details). For the estimation of flood damage (Figure 3.1: E), we used Stage-Damage Functions (SDF), Random Forests giving point estimates (RF point) and distributions (RF distribution) trained on survey data (see supplementary materials for further details). Damage estimates were computed at the municipality level (Figure 3.1: F) and validated with reported damage values from the Saxon Relief Bank.

3.3.1 The role of vulnerability uncertainty

In the first step, we compared the results from damage models providing point estimates (RF point) and models with probability distributions (RF distribution) (see Figure 1: E). To single out the effect of vulnerability uncertainty, we ignored the uncertainties originating from hazard and exposure (Figure 3.1: D; $n = 1$). The comparison shows how the damage estimation benefited from using damage model probability distributions (Figure 3.2).

The vulnerability uncertainty represents the lack of knowledge about the damage process at the object level by showing a probability. distribution of all the possible damage values for a specific object. Considering only one object, it can be seen that the point estimate, i.e. the mean, is a rather unlikely value within the skewed damage distribution (Figure 3.2, $k = 1$). Hence, in most cases the point estimate to single objects will over- or underestimate the flood damage, which results in large errors as observed in (Seifert *et al.*, 2010a; Sieg *et al.*, 2017; Wagenaar *et al.*, 2017). The higher the number of objects, by summing up their damage estimates, the better the empirical distribution fits to a normal distribution

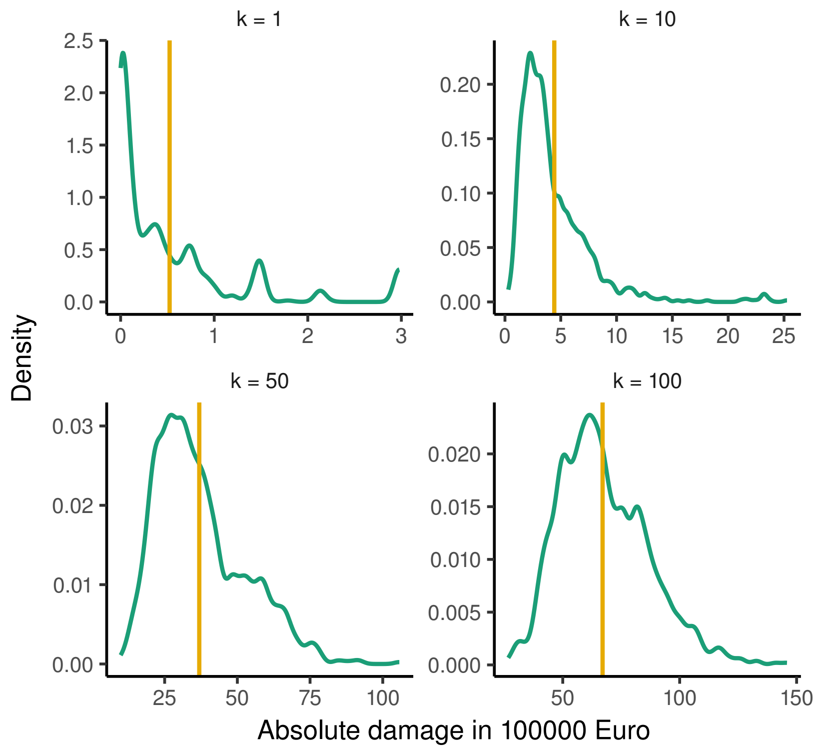

Figure 3.2: *Damage estimation for k manufacturing companies with (green; RF distribution) and without (yellow; RF point) consideration of vulnerability uncertainty. Note that the k manufacturing companies all originate from the same object set, hence the hazard and exposure uncertainty is not considered here ($n = 1$).*

(Central Limit Theorem). Hence, the larger the spatial scale (Figure 3.1: F; $k > 1$) for which the damage is estimated, the more the mean corresponds to the most likely value, but also the range of possible damage values gets proportionally wider as well (Figure 3.2).

Despite the progress in damage estimation in recent years (Schröter *et al.*, 2014; Kreibich *et al.*, 2016; Sieg *et al.*, 2017; Wagenaar *et al.*, 2017), the available damage models are not able to describe the damage process reliably and the process is stochastic to a substantial extent. Therefore, as implemented in this approach, the distribution of the damage estimate should be assessed at every spatial scale in order to report the lack of knowledge about the damage estimates.

3.3.2 Hazard and exposure uncertainty and validation

The additional inclusion of uncertainties associated with hazard and exposure and the spatial scaling of damage estimations to municipalities in Saxony results

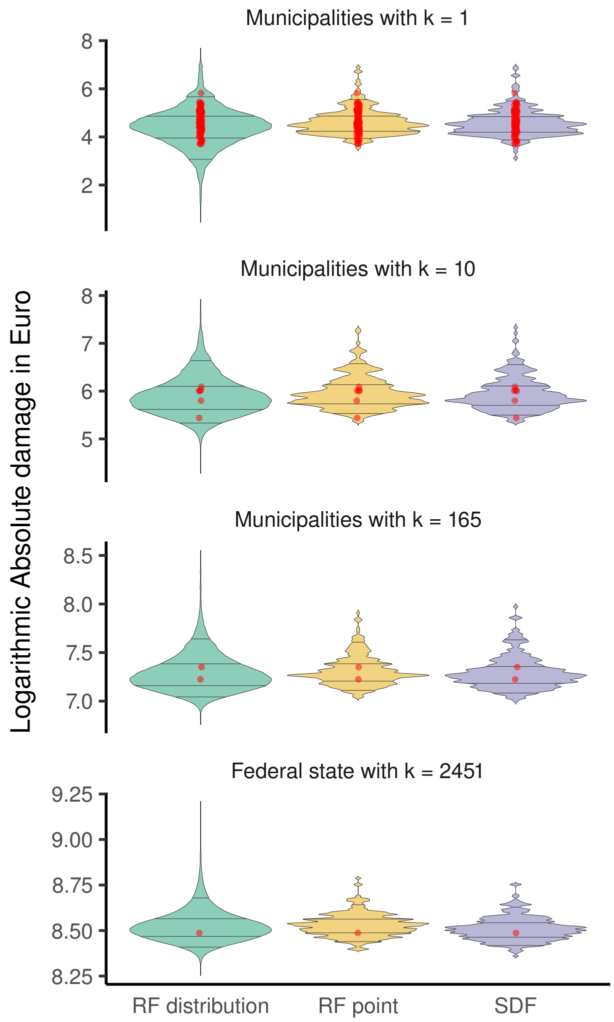

Figure 3.3: *Distribution of damage estimates with different flood damage models for municipalities with k affected objects. The red dots represent reported damages to the respective municipalities and federal states. The lines within the distributions show the 90 % and 50 % intervals, respectively.*

in a good agreement of damage estimations with reported damage values (Figure 3.3).

The estimated damage ranges are quite reliable (Figure 3.3). Depending on the flood damage model used, 90 to 97 % of the reported damage lies within the 90 % interval of the distributions and 57 to 61 % lies within the 50 % interval (Figure 3.A.1). Hence, the approach does not overestimate the uncertainties. On the contrary, it captures the diversity of reported damage values (Figure 3.3, top).

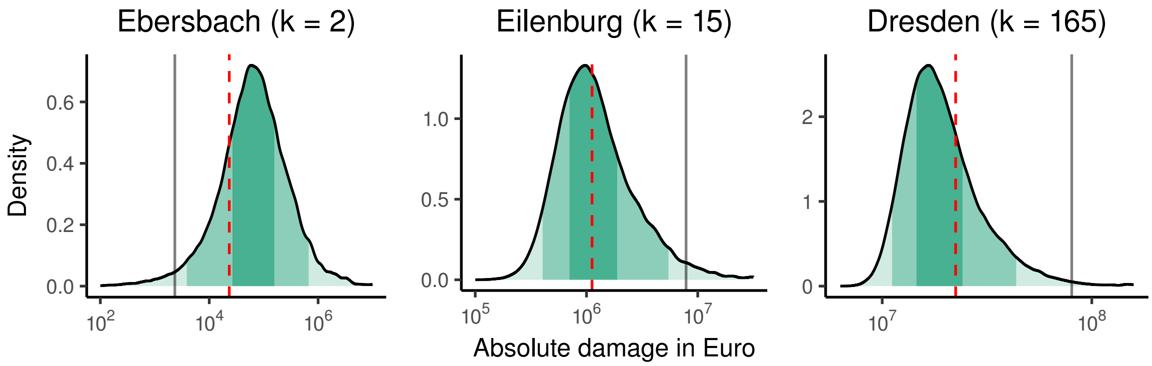

Figure 3.4: *Estimated damage distributions for the 2013 flood event for municipalities with 2, 15 and 165 affected companies (different greens indicate the 50 % and 90 % intervals). Reported values for flood damage to companies (red dashed lines) for selected municipalities and the hypothetical over- or underestimation by a factor corresponding to the estimation bias of the model FLEMOcs (Seifert* et al.*, 2010a) for the flood event in the year 2002 in the same municipality (black lines).*

In addition, the distribution of damage estimates for larger scales, e.g. cities or federal states, covers the observed damage well (Figure 3.3, center and bottom). Note that the damage models and input data type are the same for the estimation at any spatial scale, ensuring consistency without any jumps between scales. The inconsistencies in land use data and the application of the same models to different kinds of exposure data are currently weaknesses of state-of-the-art models (Jongman *et al.*, 2012a; Schwierz *et al.*, 2010; de Moel *et al.*, 2015; Prahl *et al.*, 2016).

3.3.3 Comparison of land use-based and object-based models

A comparison between damage estimations of land use-based and object-based models shows the potential for improvement with the proposed method (Figure 3.4).

Previous studies report an over- or underestimation of absolute flood damage at any spatial scale (Ward *et al.*, 2013; Winsemius *et al.*, 2013; Alfieri *et al.*, 2016b; Kreibich *et al.*, 2016; Seifert *et al.*, 2010a). At large scales, such as the global or European scale, overestimations by a factor of up to two are observed (Ward *et al.*, 2013; Alfieri *et al.*, 2016b), while at smaller spatial scales, such as municipalities or cities, even higher deviations of up to a factor of 40 are observed (Kreibich *et al.*, 2016; Seifert *et al.*, 2010a). The land use-based, multi-variable flood damage model FLEMOcs overestimated the reported flood damage to companies in Dresden during the flood event of 2002 by the factor 3.6 (Seifert *et al.*, 2010a). Considering the damage distribution for affected companies in Dresden in 2013 derived with the approach presented here, the reported damage is located in the center of the distribution, whereby a hypothetical overestimation by the factor 3.6 is located in the tail (Figure 3.4, right; see also Figure 3.3, $k = 165$, green). The same effect can be observed for smaller or less affected municipalities in cases of underestimation (Figure 3.4, left) and overestimation (Figure 3.4, center), respectively. Hence, the use of an object-based modeling approach including uncertainties results not only in a more complete picture of possible flood damage, but our results also suggest that it is more accurate compared to the widespread approach of land use based modeling. In addition, statements about the probabilities associated with certain damage ranges can be made, which is important information for decision making (Pappenberger & Beven, 2006).

3.4 Conclusions

The presented method exploits new exposure data sets, which become increasingly available due to rapid technological progress, and thus takes hydro-meteorological damage assessment to the next level. It offers seamless damage estimation across spatial scales by using object-based data at all spatial scales. The method has proven to be accurate in post-event analysis and can therefore also be used for the analysis of future risks, even more so because of the probabilistic nature of the method and the possibility of including any kind of uncertainty. Uncertainty originating from missing data or assumptions can be reflected in the results, which is of the utmost importance for future projections of risk and in data-scarce situations. Consequently, the proposed method facilitates informed risk management and decision making under consideration of uncertainties consistently at all spatial scales.

Appendix

3.A Supplementary materials

Materials and Methods

Data sets

The data sets used to train the damage models (Stage-Damage Functions and Random Forests) were taken from surveys conducted after the floods in the Elbe and Danube catchments in the years 2002 and 2013 in Germany (Kreibich *et al.*, 2005, 2007; Thieken *et al.*, 2016). The surveys were carried out by the SOKO Institute by means of computer-aided telephone interviews in October 2003, May 2004 and between May and July 2014. In total, 479 interviews were conducted for the flood in 2002 and 557 for the flood in 2013, in which the interviewed companies were chosen from a site-specific random sample based on lists of affected streets in the corresponding areas (Kreibich *et al.*, 2005). The surveys from the 2002 and 2013 floods were conducted in a comparably similar way. Questions about the following topics were asked in the surveys: flood impact parameters (e.g. contamination, water level), early warning, emergency measures, precautionary measures, company characteristics, flood damage and flood experience. The person with the best knowledge about the flood damage was questioned for each company (Kreibich *et al.*, 2005). Given answers were cross-checked during the interview to improve the data quality and to clarify contradictory answers. See (Kreibich *et al.*, 2005, 2007) for further details about the survey and the data processing.

Official statistics used to derive object (i.e. company) characteristics were taken from the German Federal Statistical Office and can be accessed via the GENESIS online data base (https://www-genesis.destatis.de/genesis/online/). Data regarding the distribution of company size classes (number of employees grouped in classes) and company sectors were taken from the German Federal Statistical Office, GENESIS table no. 52111-0003. Data on net fixed assets of buildings and equipment from different company sectors were taken from the national accounts (VGR des Bundes), GENESIS table no. 81000-0117.

Water masks were obtained from JBA Risk Management (www.jbarisk.com). Water depths in Saxony, Germany, were derived by JBA Risk Management.

Reported damage values were taken from data from the Saxon Relief Bank, which was put in charge of the loss adjustment and management in Saxony after the flood in 2013. The number of companies who applied for aid funding and the loss compensation for the damage to companies' buildings and equipment were available at the municipality level. The number of applications for aid funds to the Bank was taken as a proxy for the number of companies that were affected in the respective municipality. The damage number reported by the Saxon Relief Bank covers the damage to buildings and equipment.

Application of the method

In the presented post-event analysis of the flood event in Saxony, Germany in the year 2013 the hazard (Figure 3.1: A) is defined by a water mask from JBA Risk Management. The hazard in a pre-event analysis might be defined by expected hazard intensities for specific return periods, e.g. expected water levels or wind speed for a hundred year event.

The exposure (Figure 3.1: B) corresponds to the companies effected in Saxony in 2013. The company characteristics are defined by the sector, size and asset values of buildings and equipment. 15 company sectors from four sector groups are distinguished (Table 3.A.1).

Since the individual characteristics of the affected companies are not known, 300 variations of potentially exposed company sets are simulated by sampling the input variables for the damage models (Figure 3.1: D; $n = 300$). For each company set the number of affected companies is varied uniformly by $\pm$ 10 %. The input variables are sampled from Gamma or Multinomial distributions, which are derived from the water mask, survey data sets and official statistic data sets (Table 3.A.2). The parameters of the distribution for each input variable are provided in Table 3.A.3. The parameters of the Gamma distributions were fitted with the method of moments. The net fixed asset of a company is estimated by multiplying its number of employees with the net fixed asset value per employee of the corresponding company sector (Table 3.A.1). It is assumed that the net fixed assets of buildings and equipment per employee do not vary strongly within Germany. Yet, to account for small variations net fixed asset values are varied uniformly by $\pm$ 10 % in this application.

Two different types of damage models, namely Stage-Damage Functions and Random Forests are applied to describe the vulnerability (Figure 3.1: C and E). The complete survey data sets were used to train the models. In order to capture differences in the damaging process for the different sector groups (Table 3.A.1), four model variations are distinguished for both types of damage models, as shown in (Sieg *et al.*, 2017). While Stage-Damage Functions only use the water level for the damage prediction, table 3.A.2 lists the variables which are used in the Random Forests to predict the flood damage to buildings and equipment.

Stage-Damage Functions assign a certain damage to the water depth depending on the characteristics of the asset under consideration. The idea was first proposed in the United States (Smith, 1994) and is still considered a standard approach for estimating urban flood damage (Smith, 1994; Merz *et al.*, 2010). In Germany, stage-damage functions in the form of square-root functions (Equation 3.1) are used to estimate the relative damage to companies based on the water level at the building(Emschergenossenschaft & Hydrotec, 2004).

$$\text{damage} = a + b * \sqrt[2]{\text{water level}}. \tag{3.1}$$

They are also used in many other studies for the comparison of modeling results (Merz *et al.*, 2013; Kreibich *et al.*, 2016; Schröter *et al.*, 2014). The parameters a and b are estimated with a regression by minimizing the sum of squared residuals. In our case study, the regression is applied on the survey data, which are also used to train the Random Forests.

A Random Forest is an ensemble of decision trees, in our case regression trees, which are organized into different nodes, namely root nodes, split nodes and leaf nodes. The trees subdivide a data set by means of predictor variables into subsets that group similar values of the response variable, which in our case is the relative damage. For that purpose the split nodes provide thresholds of predictor variables to split the data set until a stop criterion is fulfilled, which is different for different algorithms. Hence, the leaf nodes correspond to data set chunks, which contain all data points for which the predictor variables meet the criteria of the corresponding split nodes. The prediction of a regression tree is provided by the leaf node that corresponds to the setting of the predictor variables. Typically, the mean value of the corresponding data set chunk of training data is returned as a predictor. The prediction of the Random Forest corresponds to a weighted average of the single tree's predictions. For a detailed introduction to Random Forests, we refer to (Breiman, 2001).

Previous studies on flood damage modeling have considered only the mean values of the leaf nodes (Merz *et al.*, 2013; Kreibich *et al.*, 2016; Hasanzadeh Nafari *et al.*, 2016c; Schröter *et al.*, 2014; Sieg *et al.*, 2017). Thus, they ignore the variation of the response variable for similar settings of the predictor variables. Alternatively, it is also possible to compute the empirical distribution of the response variable conditioned on the predictor variables (Meinshausen, 2006). In this study, we compute the conditional distributions of the relative damage (RF distribution) in addition to the conditional means (RF point). The relative damage estimates are transfered to absolute values by multiplying with the value of the net fixed assets of the corresponding company.

The spatial scaling is realized by summing up the absolute damage values for all affected companies in the considered region forming a company set (Figure 3.1: F). The summation works differently for damage models providing a distribution (e.g. RF distribution) or a point estimate (RF point) (Table 3.A.4). In the first case the damage distribution is simulated by sampling 1000 possible damage realizations ($u = 1000$) for each affected company. The realizations (q_{ij}) are represented by the columns in Table 3.A.4. The sum of the single realizations of all companies in the company set ($q_j = \sum_{i=1}^{k} q_{ij}$, sum of the columns in Table 3.A.4) corresponds to one possible composition of different damage realizations. These values ($q_j,\ j = 1, \ldots, u$) are aggregated to capture the variation of vulnerability in the results. In the second case (RF point) there is only one estimation (q_{i1}) which is summed up for the different companies in the company set. Thus the result ($q_1 = \sum_{i=1}^{k} q_{i1}$) consists of only one value without capturing the variation of vulnerability. Subsequently, this is repeated for all different versions (n) of the single companies to cover the exposure and hazard uncertainty.

Figure 3.A.1 shows damage distributions on a municipality scale with the number of affected companies increasing from $k = 1$ to $k = 195$. For each municipality damaged by the 2013 flood event in Saxony the reported damage value is plotted to the distribution with the corresponding number of affected companies, which is taken from the SAB data. The reported damage values match well with the derived distributions, even though none of them was used to derive the damage distribution.

The analysis was done with R (version 3.4.1) - a language and environment for statistical computing (R Core Team, 2017). The conditional distributions are computed following the algorithm described in (Meinshausen, 2006). The package "party" (version 1.2) was used to compute the Random Forests (Hothorn *et al.*, 2015). The package "ExtDist" (version 0.6) was used to fit the parameters of the Gamma distributions.

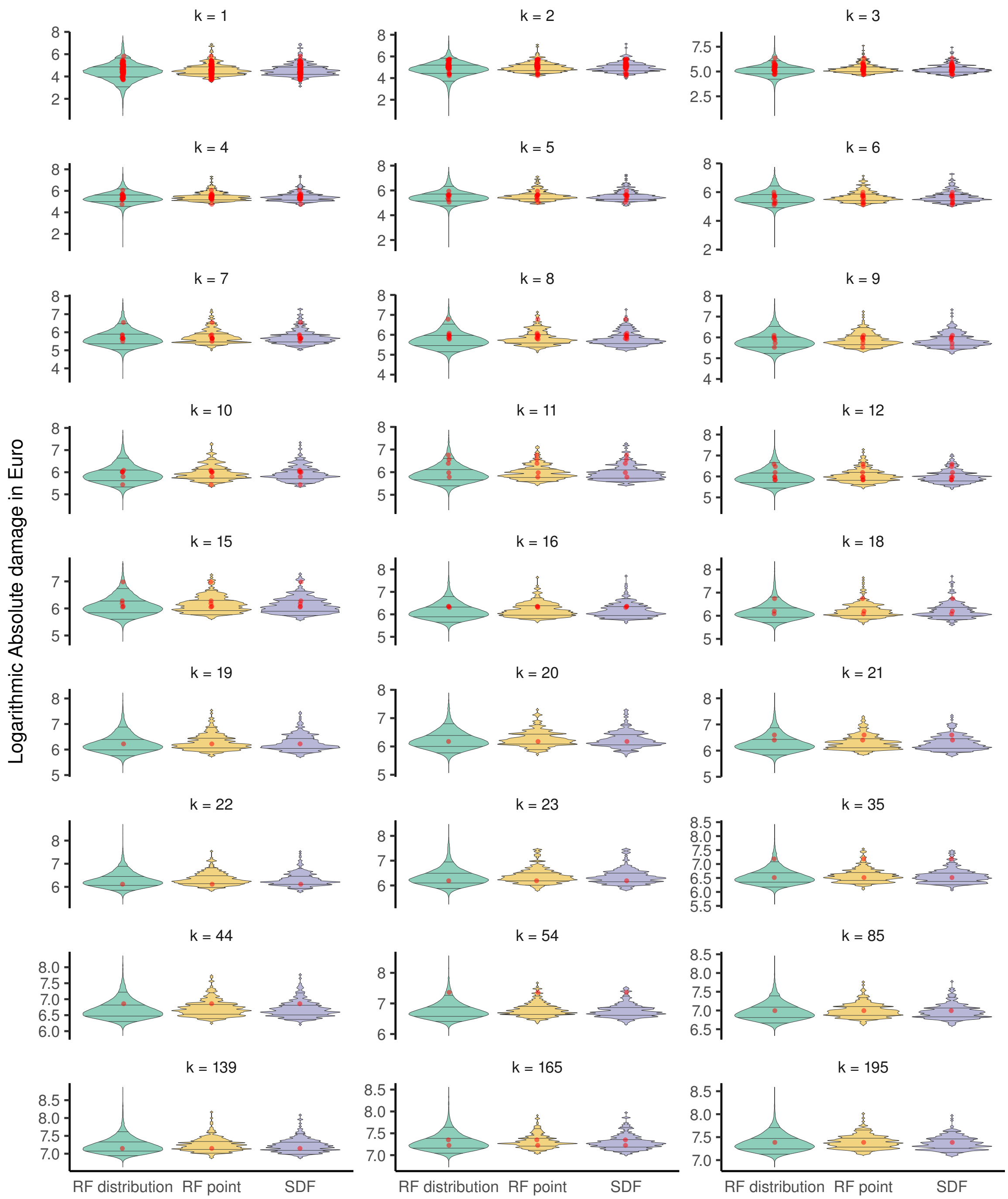

Figure 3.A.1: *Distribution of damage estimates of different methods for municipalities with k affected objects. The red dots represent reported damage in the respective municipalities. The lines within the distributions show the 90 % and 50 % intervals, respectively.*

Table 3.A.1: *Overview of economic sectors and sector groups, net fixed assets (buildings and equipment) in millions of Euros and the size in thousands of employees from different economic sectors throughout all of Germany. Different damage models are applied to the four sector groups.*

Sector group	Economic sector	buildings	equipment	size
Manufacturing				
	Manufacturing	131000	335000	7442
	Electricity, gas, steam and air conditioning supply	130000	46484	256
	Water supply; sewerage; waste managment and remediation activities	266000	19609	261
	Construction	22469	24132	2426
Commercial				
	Wholesale and retail trade repair of motor vehicles and motorcycles	134000	638000	5903
	Transporting and storage	260000	144000	2084
	Accommodation and food service activities	36600	12400	1774
Financial				
	Information and communication	37197	45259	1218
	Financial and insurance activities	129000	10426	1194
	Professional, scientific and technical activities	61343	30716	2577
	Administrative and support service activities	38016	225000	2960
Service				
	Education	253000	18024	2369
	Human health and social work activities	333000	79094	5195
	Arts, entertainment and recreation	14699	11909	644
	Other services activities	44323	13843	1488

Table 3.A.2: *Predictor and response variables used in the damage models, i.e. in the Random Forests, as well as the data sources used to derive the probability distributions for the sampling of predictor/input variables. The distributions follow a Gamma distribution for continuous variables (C) or Multinomial distribution for ordinal variables (O). Their parameters are provided in Table 3.A.3.*

	Predictor Variable	Data Source	Distribution	Values (Scale and Range)
Flood impact				
	Water level	Water mask	Gamma	C: 0 cm to 960 cm above ground
	Inundation duration	Survey	Gamma	C: 0 to 1440 h
	Contamination	Survey	Multinomial	O: 0 = no contamination to 6 = heavy contamination (7 classes)
Damage reduction				
	Adaptation ratio	Survey	Multinomial	O: 0.25 = low adaptation to 1 = high adaptation (6 classes)
	Mitigation ratio	Survey	Multinomial	O: 0.16 = low mitigation to 1 = high mitigation (11 classes)
	Emergency actions	Survey	Multinomial	O: 0 to 4 emergency measures undertaken (5 classes)
Company				
	Size	Survey	Gamma	C: 1 to 800 employees
	Size class	Official statistics	Multinomial	O: 1 = 1 - 10 employees 2 = 11 - 50 employees 3 = 50 - 250 employees 4 = $>$ 250 employees
	Sector	Official statistics	Multinomial	see economic sectors in table 3.A.1
	Spatial situation	Survey	Multinomial	O: 1 = business premises with more than one building 2 = one entire building used by the company 3 = at least one floor in an externally used building 4 = less than one floor in an externally used building
	Response Variable			
Damage				
	Relative damage of buildings	Survey		C: 0 to 1 damage ratio
	Relative damage of equipment	Survey		C: 0 to 1 damage ratio

Table 3.A.3: *Parameters for the Gamma (Γ) and Multinomial (p) distributions, which are used to sample the input variables that correspond to the simulated object versions.*

Predictor Variable	Manufacturing	Commercial	Financial	Service
Water level	$\Gamma(1.148, 0.013)$	$\Gamma(1.148, 0.013)$	$\Gamma(1.148, 0.013)$	$\Gamma(1.148, 0.013)$
Inundation Duration	$\Gamma(0.582, 0.005)$	$\Gamma(0.65, 0.005)$	$\Gamma(0.972, 0.008)$	$\Gamma(0.772, 0.005)$
Contamination	$p(0.33, 0.29, 0.01, 0.11, 0.13, 0.01, 0.12)$	$p(0.42, 0.22, 0.01, 0.08, 0.13, 0.02, 0.12)$	$p(0.45, 0.20, 0.03, 0.11, 0.10, 0.01, 0.10)$	$p(0.44, 0.29, 0.01, 0.07, 0.10, 0.0, 0.09)$
Mitigation	$p(0.04, 0.08, 0.14, 0.27, 0.04, 0.25, 0.03, 0.07, 0.02, 0.01, 0.00, 0.04)$	$p(0.04, 0.05, 0.10, 0.26, 0.02, 0.35, 0.01, 0.05, 0.03, 0.01, 0.01, 0.07)$	$p(0.05, 0.04, 0.11, 0.31, 0.01, 0.35, 0.00, 0.04, 0.02, 0.01, 0.00, 0.06)$	$p(0.08, 0.05, 0.16, 0.25, 0.01, 0.29, 0.02, 0.05, 0.02, 0.01, 0.01, 0.05)$
Adaptation	$p(0.21, 0.29, 0.17, 0.04, 0.03, 0.26)$	$p(0.11, 0.22, 0.24, 0.05, 0.01, 0.37)$	$p(0.10, 0.33, 0.24, 0.06, 0.01, 0.26)$	$p(0.16, 0.27, 0.22, 0.04, 0.01, 0.30)$
Emergency actions	$p(0.45, 0.32, 0.16, 0.06, 0.01)$	$p(0.49, 0.35, 0.12, 0.03, 0.01)$	$p(0.55, 0.30, 0.13, 0.01, 0.01)$	$p(0.39, 0.34, 0.21, 0.05, 0.01)$
Size	$\Gamma(0.237, 0.005)$	$\Gamma(0.208, 0.016)$	$\Gamma(0.159, 0.014)$	$\Gamma(0.296, 0.015)$
Spatial situation	$p(0.48, 0.31, 0.15, 0.06)$	$p(0.21, 0.30, 0.37, 0.12)$	$p(0.06, 0.23, 0.44, 0.27)$	$p(0.29, 0.19, 0.31, 0.21)$

Table 3.A.4: *The summation of damage realizations sampled from the damage distributions (RF distribution) or obtained from point estimations (RF point) of k objects in an object set.*

		RF distribution Damage realizations					RF point Point estimate
		1	...	j	...	u	1
Companies	1						
	...						
	i			q_{ij}			q_{i1}
	...						
	k						
Total Damage	$\sum_{i=1}^{k}$			q_j			q_1

4 Integrated assessment of short-term direct and indirect economic flood impacts including uncertainty quantification

Abstract

Understanding and quantifying total economic impacts of flood events is essential for flood risk management and adaptation planning. Yet, detailed estimations of joint direct and indirect flood-induced economic impacts are rare. In this study an innovative modeling procedure for the joint assessment of short-term direct and indirect economic flood impacts is introduced. The procedure is applied to 19 economic sectors in eight federal states of Germany after the flood events in 2013. The assessment of the direct economic impacts is object-based and considers uncertainties associated with the hazard, the exposed objects and their vulnerability. The direct economic impacts are then coupled to a supply-side Input-Output-Model to estimate the indirect economic impacts. The procedure provides distributions of direct and indirect economic impacts which capture the associated uncertainties. The distributions of the direct economic impacts in the federal states are plausible when compared to reported values. The ratio between indirect and direct economic impacts shows that the sectors Manufacturing, Financial and Insurance activities suffered the most from indirect economic impacts. These ratios also indicate that indirect economic impacts can be almost as high as direct economic impacts. They differ strongly between the economic sectors indicating that the application of a single factor as a proxy for the indirect impacts of all economic sectors is not appropriate.

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Submitted as:
Sieg T, Schinko T, Vogel K, Mechler R, Merz B, Kreibich H. Integrated Assessment of short-term direct and indirect economic Flood Impacts including Uncertainty Quantification. PLOS One.

4.1 Introduction

Flood events can have multiple impacts on economic sectors at all scales of an affected region. Those are not limited to direct impacts on companies, which commonly occur inside the flooded areas, but also include indirect impacts across economic sectors, which typically occur outside the flooded regions (Jonkman *et al.*, 2008; Merz *et al.*, 2010), by e.g. affecting other companies due to disruptions in the production chain. Comprehensive impact assessments that capture both, direct and indirect economic impacts, are needed to inform flood risk management (Klijn *et al.*, 2015; Vorogushyn *et al.*, 2018) and are increasingly demanded by decision makers (Meyer *et al.*, 2013; Pfurtscheller & Vetter, 2015). Relying on cost-benefit analyses that exclude indirect economic impacts may lead to sup-optimal decisions (Kreibich *et al.*, 2014; Wagenaar *et al.*, 2016). Yet, integrated assessments of direct and indirect economic impacts on companies and economic sectors are rarely conducted (Koks *et al.*, 2015).

The most common approach to estimate direct flood damage to buildings goes back to Grigg & Helweg (1975), who related the water level at the buildings to the damage caused by the flood. These so-called depth-damage curves consider the water level as the only parameter and are the base of many flood damage models (Smith, 1994; MURL, 2000; Emschergenossenschaft & Hydrotec, 2004; Scawthorn *et al.*, 2006). Recently, multi-variable models consider additional parameters, e.g. precautionary measures, building type or contamination, to improve the description of the damage processes (Hasanzadeh Nafari *et al.*, 2016b; Merz *et al.*, 2013; Kreibich *et al.*, 2010; Penning-Rowsell *et al.*, 2005; Thieken *et al.*, 2008). However, most of these approaches estimate the damage to private households and only a few methods aim to predict flood damage suffered by companies (Gerl *et al.*, 2016). Recent advances introduced tree-based models for the estimation of flood damage to different company assets, i.e. buildings, equipment, and goods and stock (Sieg *et al.*, 2017). It has also been shown that a sector-specific consideration of flood damage increases the model performance, suggesting that direct economic impacts should be assessed separately for different economic sectors (Sieg *et al.*, 2017).

The performance of models estimating the direct economic flood impacts to companies is generally low (Seifert *et al.*, 2010b; Sieg *et al.*, 2017), and uncertainty assessments are needed for evaluating the model reliability. Yet, uncertainties associated with the estimation of direct economic impacts are rarely quantified (Merz *et al.*, 2010). A recent study proposes the use of multi-model ensembles to combine estimations from different models of the same class aiming to capture the uncertainties (Figueiredo *et al.*, 2018). However, this covers only the uncertainties associated with the model setup and the parameter estimation, while other components such as the water level or the exposure data also contribute to the overall uncertainties (de Moel & Aerts, 2011).

Another source for inaccurate estimates of direct economic impacts is the inconsistent handling of spatial scales. Direct economic impacts can be estimated at different spatial scales (de Moel *et al.*, 2015), which can be divided into the object, regional and national level. Most models are derived at the object level, but applied at the regional level using different kinds of exposure data, e.g. land use data sets at the regional level versus building data sets at the local level. This leads to inconsistent methodologies across scales (Sieg *et al.*, 2018). In addition, these land use data sets suffer from inconsistencies themselves, such as varying density of objects within an area, which is not detected by the land use data (Jongman *et al.*, 2012a).

Yet, the assessment of direct economic flood impacts on the national scale is still mostly conducted on the basis of land use (Gerl *et al.*, 2016). One example for the use of individual objects on the regional scales is the study of Huttenlau *et al.* (2010) who assessed direct economic flood impacts in Tyrol, Austria. However, the uncertainties associated with the estimations are not considered. Saint-Geours *et al.* (2015) attempt to assess uncertainties e.g. associated with depth-damage curves and the hazard maps in a probabilistic framework, while using a land use data set instead of single objects for the exposure. The method used in this study combines the object-based approach with a probabilistic attempt to take all uncertainties associated with the estimation of direct economic impacts into account and represent them within the results (Sieg *et al.*, 2018).

Indirect economic impacts of natural hazards are mostly assessed with macroeconomic models that describe interactions between different economic sectors as well as the public sector, e.g. Input-Output (IO) models and Computable General Equilibrium (CGE) models (Meyer *et al.*, 2013). IO and CGE models are usually applied at the regional or national scale. For example, Santos & Haimes (2004) developed a so-called inoperability model based on the IO analysis to estimate the production loss of an economic system resulting from unexpected events. Rose & Liao (2005) applied a CGE model to assess the resilience of regional economies to disasters.

These macroeconomic modeling techniques have also been used for assessing flood impacts. For example, Hallegatte (2008) developed an adaptive regional IO model to estimate the indirect economic impacts caused by Hurricane Katrina. Mochizuki *et al.* (2015) estimated the follow-on impacts of a flood in Cambodia with an IO based inter-industry economic model, and Carrera *et al.* (2015) used a CGE model (Standardi *et al.*, 2014) to assess indirect economic impacts caused by a flood event of the Po river in Italy.

However, most flood impact assessments neglect indirect economic impacts

(Rojas *et al.*, 2013; Merz *et al.*, 2010). Some models, as e.g. the Damagescanner, include indirect impacts simply as a certain percentage of the direct economic impact (Ward *et al.*, 2011). Furthermore, IO and CGE models incorporate damage estimates from direct impact assessments only as exogenous point-estimated parameters. Only few studies aim to directly link the estimation of direct economic impacts with the assessment of indirect economic impacts. The existing approaches mainly use land use-based single parameter models, as the depth-damage curves, to estimate the direct damage caused to a system. Thus, Koks *et al.* (2015) and Jonkman *et al.* (2008) couple depth-damage curves with IO based models, whereas Carrera *et al.* (2015) link depth-damage functions with CGE models. These approaches, however, largely ignore uncertainties associated with the estimation of direct economic impacts, since they typically only perform a sensitivity analysis over a rather limited number of exogenous direct damage estimates. Moreover, these models are not able to capture spatial inconsistencies, which typically occur in the exposure data sets such as land use data (de Moel *et al.*, 2015; Prahl *et al.*, 2016). So far, a coupling procedure which quantifies and finally forwards the uncertainties associated with the estimation of the direct economic impacts to the estimation of the indirect economic impacts within one methodological approach is missing.

Therefore, this study develops a novel procedure for a comprehensive quantitative assessment of economic flood impacts that (1) includes uncertainties associated with the estimation of direct impact (Sieg *et al.*, 2018) and (2) subsequently links these impacts to a macroeconomic IO-based assessment of indirect economic impacts. In the case of extreme event risk, the short-term indirect economic spillover effects caused by supply-side shocks are of particular interest. Hence, a supply-side IO model is chosen, since it is more applicable to capture short-term economic impacts than e.g. a CGE model (Okuyama & Santos, 2014). Short-run substitution and price elasticities, as used in the CGE models, are close to zero for short-term assessments (Rose & Guha, 2004) making CGE models more complicated to apply for the estimation of short-term impacts (Oosterhaven, 2017).

The study focuses on two main aspects. The first aspect is the application of seamless estimation and uncertainty quantification of direct economic flood impacts to the national level by means of newly available exposure data sets. The second aspect is the linkage between the estimation of the direct and indirect economic flood impacts on a national level, including the uncertainties associated with the estimation of the direct economic impacts.

4.2 Data & Methods

Figure 4.1 shows the procedure developed in this study and the data sets used. The procedure is applied to the flood event in 2013 in Germany, which caused severe impacts and affected large parts of the country along the rivers Elbe and Danube for several weeks (Merz *et al.*, 2014; Schröter *et al.*, 2015; Thieken *et al.*, 2016). In the following, the estimation of the direct economic impacts is described, followed by the presentation of the estimation of the indirect impacts and of the linkage between direct and indirect damages. R (version 3.4.1) - A language and environment for statistical computing (R Core Team, 2017) is used for all analyses and figures and for the implementation of the whole procedure.

4.2.1 Direct economic impacts

Direct economic impacts are estimated by the probabilistic, object-based approach developed by (Sieg *et al.*, 2018). Tree-based damage models (Sieg *et al.*, 2017) are used to compute the relative damage to single companies. To transfer relative to absolute damage the net fixed assets per company are estimated. The first row in Figure 4.1 shows the used data sets and how they contribute to the prediction of direct economic impact.

Data sets

Twelve federal states were affected during the flood event in 2013. For this study the eight federal states along the catchments of the rivers Danube and Elbe are considered, which were most affected by extensive flooding (Schröter *et al.*, 2015; Thieken *et al.*, 2016). This comprises the federal states Bavaria, Brandenburg, Lower Saxony, Mecklenburg, Saxony, Saxony-Anhalt, Schleswig-Holstein and Thuringia, which suffered more than 98 % of the overall direct economic impacts in Germany (Thieken *et al.*, 2016).

The flooded area and the related water depths are taken from a water mask provided by JBA Risk Management (http://www.jbarisk.com). A data base of single buildings in Germany is extracted from openstreetmap.org (OSM). Only buildings with an occupancy related to a commercial, educational, industrial, public or mixed use are counted for the number of affected companies in the federal states. Buildings related to infrastructure, government or gathering venues are excluded for the counting.

Official statistics, taken from the German Federal Statistical Office, are used to derive the characteristics (size, economic sector, net fixed assets) of companies in different federal states. The data sets can be accessed via the GENESIS online

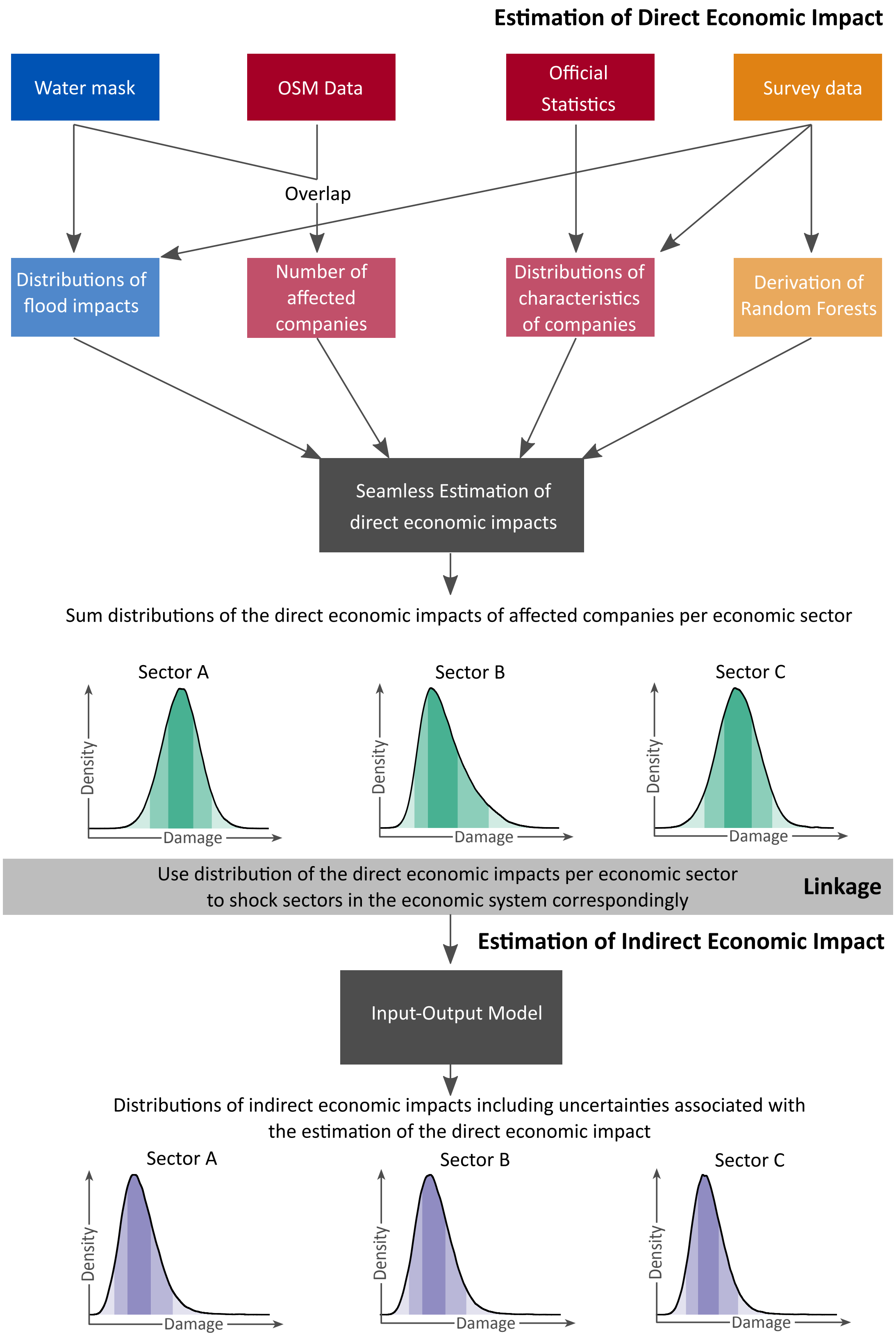

Figure 4.1: *Modeling procedure and data sets (darker colours) used to derive inputs (brighter colours) for the hazard (blue), exposure (red) and vulnerability (orange) used by the method for the computation of the direct (green) and indirect (purple) economic impacts.*

Table 4.1: *Economic sectors and sector groups, net fixed assets (buildings and equipment) in millions of Euros and the size in thousands of employees for different economic sectors throughout all of Germany. Different damage models are applied to the four sector groups.*

Sector group	Economic sector	buildings	equipment	size
Manufacturing				
	Manufacturing	131000	335000	7442
	Electricity, gas, steam and air conditioning supply	130000	46484	256
	Water supply; sewerage; waste management and remediation activities	266000	19609	261
	Construction	22469	24132	2426
Commercial				
	Wholesale and retail trade repair of motor vehicles and motorcycles	134000	638000	5903
	Transporting and storage	260000	144000	2084
	Accommodation and food service activities	36600	12400	1774
Financial				
	Information and communication	37197	45259	1218
	Financial and insurance activities	129000	10426	1194
	Professional, scientific and technical activities	61343	30716	2577
	Administrative and support service activities	38016	225000	2960
Service				
	Education	253000	18024	2369
	Human health and social work activities	333000	79094	5195
	Arts, entertainment and recreation	14699	11909	644
	Other services activities	44323	13843	1488

data base (https://www-genesis.destatis.de/genesis/online/). Data regarding the distribution of company size classes (number of employees grouped in classes) and economic sectors separated by different federal states are taken from the German Federal Statistical Office, GENESIS Table no. 52111-0003. Net fixed assets of buildings and equipment from different economic sectors are taken from the national accounts (VGR des Bundes), GENESIS Table no. 81000-0117. Table 4.1 shows the net fixed assets of buildings and equipment and the number of employees of different economic sectors. Table 4.2 shows the distribution of companies among the different economic sectors and size classes.

A survey data set, collected in the aftermath of flood events in Germany, is used to derive models predicting direct economic flood impacts and to derive distributions used for the seamless estimation (Table 4.3). See Kreibich *et al.* (2005, 2007) for further details about the survey and the data processing as well as Sieg *et al.* (2017) for the development of the tree-based models and a basic statistical analysis of the data sets.

Table 4.2: *Percentages of companies in different size classes and economic sectors in the eight federal states.*

Sectorname	1-10	11-50	51-250	>250	total
Manufacturing	5,506	1,370	0,471	0,112	7,46
Electricity, gas, steam and air conditioning supply	2,490	0,026	0,016	0,005	2,54
Water supply; sewerage; waste management and remediation activities	0,301	0,090	0,030	0,003	0,42
Construction	12,260	1,14	0,103	0,008	13,51
Wholesale and retail trade repair of motor vehicles and motorcycles	17,900	1,560	0,245	0,039	19,74
Transporting and storage	3,068	0,486	0,095	0,013	3,66
Accommodation and food service activities	6,985	0,468	0,052	0,004	7,51
Information and communication	3,071	0,223	0,056	0,009	3,36
Financial and insurance activities	2,003	0,045	0,036	0,020	2,10
Professional, scientific and technical activities	13,048	0,661	0,080	0,013	13,80
Administrative and support service activities	5,628	0,408	0,143	0,032	6,21
Education	1,844	0,380	0,059	0,010	2,29
Human health and social work activities	6,137	0,860	0,239	0,065	7,30
Arts, entertainment and recreation	2,677	0,093	0,016	0,003	2,79
Other services activities	6,938	0,288	0,051	0,008	7,29

Table 4.3: *Input variables used by the Random Forests for the estimation of the direct economic impacts and the distributions used to simulate these variables as well as data sources.*

	Input Variable	Data Source	Distribution
Flood characteristics			
	Water level	Water mask	Gamma
	Inundation Duration	Survey	Gamma
	Contamination	Survey	Multinomial
Company characteristics			
	Mitigation	Survey	Multinomial
	Adaptation	Survey	Multinomial
	Emergency actions	Survey	Multinomial
	Size	Survey	Gamma
	Size class	Official statistics	Multinomial
	Sector	Official statistics	Multinomial
	Spatial situation	Survey	Multinomial

Estimation of direct economic impacts

Direct economic impacts are estimated at the object level. They are determined by hazard, exposure and vulnerability characteristics. Here, the hazard is represented by the water level, inundation duration and contamination at the companies during the flood event in 2013 in Germany. The exposure consists of the number of affected companies, the characteristics of the companies (size, economic sector, precaution etc.) and the asset values of the companies. The vulnerability is described by a tree-based damage model.

Since the individual characteristics of the affected companies are unknown, the broad range of individual specifications was reflected by sampling company characteristics from distributions derived by a water mask, official statistics and survey data. Table 4.3 shows the input variables (predictors) used for the damage modeling as well as the data sources and distributions, which are used to sample the predictors. The parameters of the distributions can be obtained from Sieg *et al.* (2018). The flood impact at each company is sampled from distributions derived from the water mask and survey data, whereby the water level is taken from the water mask and the inundation duration as well as the contamination are taken from the survey data.

The number of directly affected companies in each federal state is determined by an overlap of the water mask and the OSM data. The affiliation of single companies to specific economic sectors is sampled from official statistics. Company characteristics, such as precautionary measures or the size of a company, are sampled from official statistics and survey data. The net fixed assets of a company are calculated by multiplying the number of employees with the net fixed asset value per employee of the corresponding economic sector (Table 4.1). It is assumed that the net fixed assets of buildings and equipment per employee do not vary strongly within Germany. However, to account for small variations net fixed asset values are varied uniformly by $\pm$ 10 %. 1000 versions of affected company sets are sampled for each federal state to simulate the distribution of the input variables. This procedure is in contrast to state-of-the-art models using land use data, which typically use the mean value of the input variables and thus ignore the variability of the exposed assets.

For each of the sampled company version the relative damage is estimated with a tree-based model, that is derived from the survey data collected after the 2002 and 2013 flood events (Sieg *et al.*, 2017). Individual damage models are used for the four sector groups (Table 4.1), that are formed according to the European statistical classification of economic activities in the European Community (NACE Rev. 2; Nomenclature statistique des Activites economiques dans la Communaute Europenne) (Eurostat, 2008). In total, eight different Random Forests are grown -

following the algorithm of Hothorn *et al.* (2006) - to consider the four different economic sector groups (1) manufacturing, (2) commercial, (3) financial and (4) service, as well as two different types of assets (a) buildings and (b) equipment. We refer to Sieg *et al.* (2017) for a detailed description of the application of the Random Forest approach for the estimation of direct economic flood impacts to companies. For a general introduction to Random Forest we refer to Breiman (2001).

Previous studies on tree-based flood damage models usually take the mean value of observations with comparable input variables as an estimator for the relative damage (Merz *et al.*, 2013; Kreibich *et al.*, 2016; Hasanzadeh Nafari *et al.*, 2016c; Schröter *et al.*, 2014; Sieg *et al.*, 2017). They consequently ignore the large variation of damage realizations, that are typically observed for comparable input variables. Here we aim to capture the uncertainty related to the prediction of the direct economic impacts and follow the algorithm of Meinshausen (2006) to obtain a distribution of direct economic impacts instead of a point estimate.

The probability distributions for the relative damage of a single company is transferred to absolute values by multiplying the relative damage with the net fixed asset values. To obtain the direct economic impact per federal state, the absolute values of the damage distributions are summed up. Similarly, the direct economic impacts to individual economic sectors can be estimated by summing up absolute economic impact estimates for the affected companies in the corresponding sector. The latter distributions are used to shock the IO model, as illustrated in Figure 4.1.

4.2.2 Indirect economic impacts

A national IO table of the economy of Germany for the year 2013 was obtained from the German Federal Statistical Office. On this basis a supply-side IO model was used to compute the indirect economic impacts.

Input-Output tables

The IO table, taken from the German Federal Statistical Office, can be accessed via the GENESIS online data base with the table no. 81511-0003. It consists of 72 economic sectors. For this study the table was aggregated to 19 economic sectors following NACE Rev. 2 according to the European statistical classification of economic activities in the European Community (Eurostat, 2008): Agroforestry; Mining and Quarrying; Manufacturing; Electricity, Gas, Steam, and Air Conditioning Supply; Water Supply, Sewerage, Waste Management and Remediation Activities; Construction; Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles; Transportation and Storage; Accommodation and Food Service Activities; Information and Communication; Financial and Insurance Activities; Real Estate Activities; Professional, Scientific and Technical Activities; Other Economic Activities; Administrative and Support Service Activities; Education; Human Health and Social Work Activities; Arts, Entertainment and Recreation; other Service Activities.

Input-Output models

IO models originate from the work on economic problems of Wassily Leontief (Leontief, 1986). The core of an IO model is observed data which reflects economic activities between different producing sectors. Table 4.4 shows a schematic IO table, consisting of the intermediate flows **Z** of values/products between the sectors, which are producing and purchasing the products to each other. Traditionally, Input-Output models can be used to estimate the changes of the inputs x_j resulting from a change in the outputs x_i, e.g. final demand f. This can be estimated as follows:

$$x = (I - A)^{-1} f \tag{4.1}$$

with $A = \mathbf{Z}\hat{x}^{-1}$ and $\hat{x}$ as the diagonal matrix of x, whereby $(I - A)^{-1}$ is known as the so-called Leontief inverse. This model is often referred to as demand-side IO model.

Ghosh (1958) introduced the alternative IO model, which can be used to estimate the change of the outputs x_i resulting from a change of the inputs x_j, e.g. the capital stock K_j by changing the "column-wise" view of the demand-side model to a "row-wise" view.

$$x = (I - B)^{-1} v \tag{4.2}$$

with $B = \hat{x}^{-1} Z$.

For a comprehensive introduction of demand-side and supply-side IO models see Miller & Blair (2009).

Originally, the changes estimated by supply-side models were interpreted as physical output changes, which was critized as implausible by several authors (Dietzenbacher, 1997; Oosterhaven, 1988). A reinterpretation of the supply-side model by Dietzenbacher (1997) as a price model instead of a quantity model allowed for a meaningful use of the models. In this interpretation the quantities remain fixed and only the price of the outputs changes with a change in the inputs.

In this study the Ghosh-price model is used to estimate the impacts caused

Table 4.4: *Schematic Input-Output Table with* **Z** *denoting the intermediate flow matrix, the final demand f, the capital stock K, labour L and imports m.*

		Purchasing Sectors						
		1	...	j	...	n	Final Demand	Total Output ($\mathbf{x}$)
Producing Sectors	1							
	...							
	i			$\mathbf{Z}$			f	x_i
	...							
	n							
Payments Sector	Value added ($\mathbf{v}'$)			K_j				K
				L_j				L
	Imports			m_j				M
Total outlays ($\mathbf{x}'$)				x_j				X

by a change of the capital stock resulting from a flood event on the outputs of an economy expressed as the change in prices.

In general, most IO case studies do not include uncertainty analyses (Lenzen *et al.*, 2010). Although, uncertainties due to e.g. errors in the collected data to the estimation of trade flows should not be ignored (Temurshoev, 2017). Also this study does not explicitly include uncertainties associated with the estimation of the indirect impacts, as the focus of this study has been more in the direction of linking the models including the uncertainties associated with estimation of the direct impacts. In theory the inclusion of uncertainties associated with the indirect impacts can be carried out, as suggested by Temurshoev (2017), by e.g. perturbing the flow matrix similar to Bullard & Sebald (1977). This way, ranges of outputs reflecting possible variations of the trade flows can be obtained. However, this is only one possibility to approach this issue, many more such as the derivation of a probability density function of the Leontief inverse, are listed in Temurshoev (2017).

4.2.3 Linkage of direct and indirect economic impacts

Direct economic impacts of all federal states are aggregated for each economic sectors for whole Germany. Distributions of direct economic impact estimates for each of the 1000 different company versions, and therefore sector versions, are used to shock the IO model. Hence, the IO model is shocked 1000 times using 1000 direct economic impact distributions per economic sector in Table 4.1. Each direct economic impact distribution is represented by 1000 samples from the corresponding distribution. Subsequently, the approach described in the following is repeated 1000*1000 times for each economic sector covering all uncertainties associated with the direct economic impact estimation.

The calculated direct economic impact per sector is used as input to the Ghosh-price model to estimate the indirect economic impacts. The direct economic flood impact D_j is assumed to affect the capital stock of every economic sector K_j directly. The flood impacts on the capital stock of the companies are calculated as follows:

$$K_j^s = K_j - D_j \tag{4.3}$$

In a next step the value added v is recalculated by a summation of the labor L and the shocked capital stock K^s:

$$v^s = L + K^s \tag{4.4}$$

The shocked value added v^s is then used to calculate the outputs x^s shocked by the flood event with:

$$x^s = (I - B)^{-1} v^s \tag{4.5}$$

Since these results reflect the direct as well as the indirect economic impacts, a further differentiation between these two impacts is necessary. This is done by the subtraction of the direct from the indirect economic impacts before calculating the price changes.

$$x_j^{s1} = (x_j - x_j^s) - D_j \tag{4.6}$$

Consequently, the price change Δx can be estimated as:

$$\Delta x_j = x_j^{s1} / x_j \tag{4.7}$$

In this case Δx_j shows the decrease of output prices caused by an decrease of the inputs. This can be interpreted as the price decrease, which affected sectors have to compensate for.

4.3 Results & Discussion

First, the results of the identification of affected buildings and the estimates of the direct economic impact on companies of individual federal states as well as for the single economic sectors are presented and discussed. Second, the estimates of the indirect economic impacts and ratios between indirect and direct economic impact are shown.

4.3.1 Direct economic impacts divided by federal states

A total of 11382 companies affected by the flood in the eight federal states are identified by the overlap of the water mask with the OSM data (Figure 4.2). The Saxon Relief Bank, being responsible for the loss adjustment and management in Saxony after the flood in 2013, received about 2450 damage claims of companies. This number corresponds well with the number of 2548 affected companies identified in Saxony by means of the water mask and the OSM data (Figure 4.2). Comparable numbers for the other federal states are not available, but it is expected that this approach works equally well for all other federal states. Hence, in this case it can be assumed that the identification of flood affected buildings in Germany works reliably.

The overall direct economic impact to companies' buildings and equipment is estimated per federal state (Figure 4.2). The distributions of the estimated direct economic impacts show the range of possible values. They reflect the uncertainties associated with the estimation of the direct economic impact. For example, the 50 % interval (dark green) of the direct economic impacts suffered by companies in the federal state Saxony indicates an absolute direct economic impact between 300 and 380 million Euro, while the 90 % interval (light green) indicates an absolute direct economic impact between 270 and 510 million Euro. Hence, according to these estimations there is a 90 % probability that the direct economic impact lies between 270 and 510 million Euro. The higher the number of affected companies is in a federal state, the higher the corresponding direct economic impacts and the broader the ranges. The federal states Bavaria, Saxony-Anhalt and Saxony suffered the highest direct economic impact, whereby Schleswig-Holstein and Lower Saxony suffered the lowest direct economic impact. This is in accordance with the reported numbers published by the Federal Ministry of the Interior (Bundesministerium des Innern, 2013).

Generally, data for validation of estimated direct economic impact is scarce (Merz *et al.*, 2010). Therefore, reports of the Federal Ministry of Finance are used as benchmarks for a validity check (Thieken *et al.*, 2016). These reports show mostly overall direct economic impacts per federal state including direct

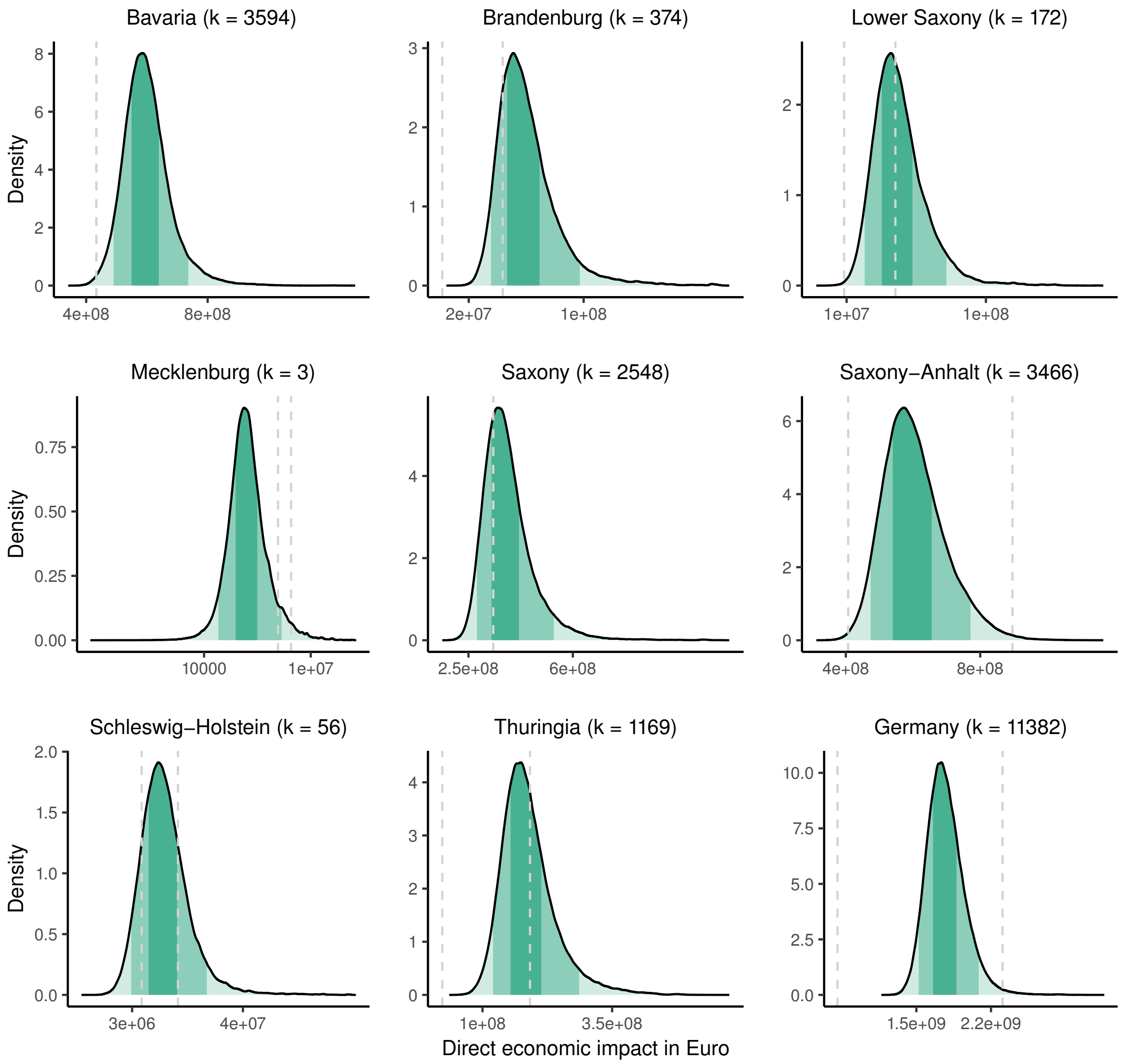

Figure 4.2: *Distributions of estimated direct economic impact for k affected companies in the respective federal states. The gray dashed lines indicate the range of the assumed direct economic impact from reports of the respective federal states (Thieken* et al.*, 2016). The different greens indicate the 50 % and 90 % intervals.*

economic impacts to the sectors private households, industrial and commercial sector, agriculture and forestry as well as state and municipal infrastructure. Data about the share of the reported impacts by the different sectors is only available for the federal states Bavaria and Saxony. The share of the industrial and commercial sector to overall economic impacts ranges between about 15 and 35 % (Thieken *et al.*, 2016). Hence, this range was taken to check the validity of the estimated direct economic impacts to companies (gray dashed lines in Figure 4.2). For Bavaria the reported 32.4 % of 1308 million Euro is taken as validity point and for Saxony the reported claims of companies amounting to about 306 million Euro to the Saxon Relief Bank is used. Note that these reported values are also prone to uncertainties and only give an rough idea about the direct economic impacts.

The validity check shows that ranges reported for each of the eight federal states lie within the distributions of estimated direct economic impact of the respective federal state. In some federal states, e.g. Bavaria and Brandenburg, the reported values are located towards the left tail of the distributions, suggesting an overestimation of the direct economic impacts. However, the derived percentages of 15 and 35 % cover only the industrial and commercial sector, whereas the estimated direct economic impacts also cover service sectors such as education or arts, entertainment and recreation and partly infrastructure sectors such as electricity, gas, steam and air conditioning supply (Table 4.1). Therefore, the estimated impacts are expected to be higher than the values of the validity check, and we conclude that the distributions of the estimated direct economic impacts per federal state are plausible.

4.3.2 Direct economic impacts divided by economic sectors

The method of Sieg *et al.* (2018) allows not only a spatial scaling (in this case to federal states), but also a thematic grouping, e.g. to economic sectors. Figure 4.3 shows the estimated direct economic impacts summed up to economic sectors over all eight federal states representing about 98 % of the overall loss in Germany during the event. Data for a validity check with regard to direct impacts to the economic sectors for whole Germany was not available.

The distributions of the direct impacts vary widely between the sectors. The variation in the range is mainly caused by different asset values (Table 4.1) and company characteristics (Table 4.3). The difference in the location can be explained by the different asset values of the economic sectors and the number of companies of the respective sector in the federal states (Table 4.2).

Economic sectors which suffered the highest direct economic impacts are the Manufacturing, Electricity, gas, steam, and air conditioning supply, Water supply, sewerage, waste management and remediation activities, and Transportation and storage. These results seem plausible, since manufacturing companies are the most common and the asset values per employee of the other three economic sectors are high (Table 4.1). The lowest impacts are estimated for the sectors Arts, entertainment and recreation, as well as service activities which agrees with the comparatively low asset values of these sectors.

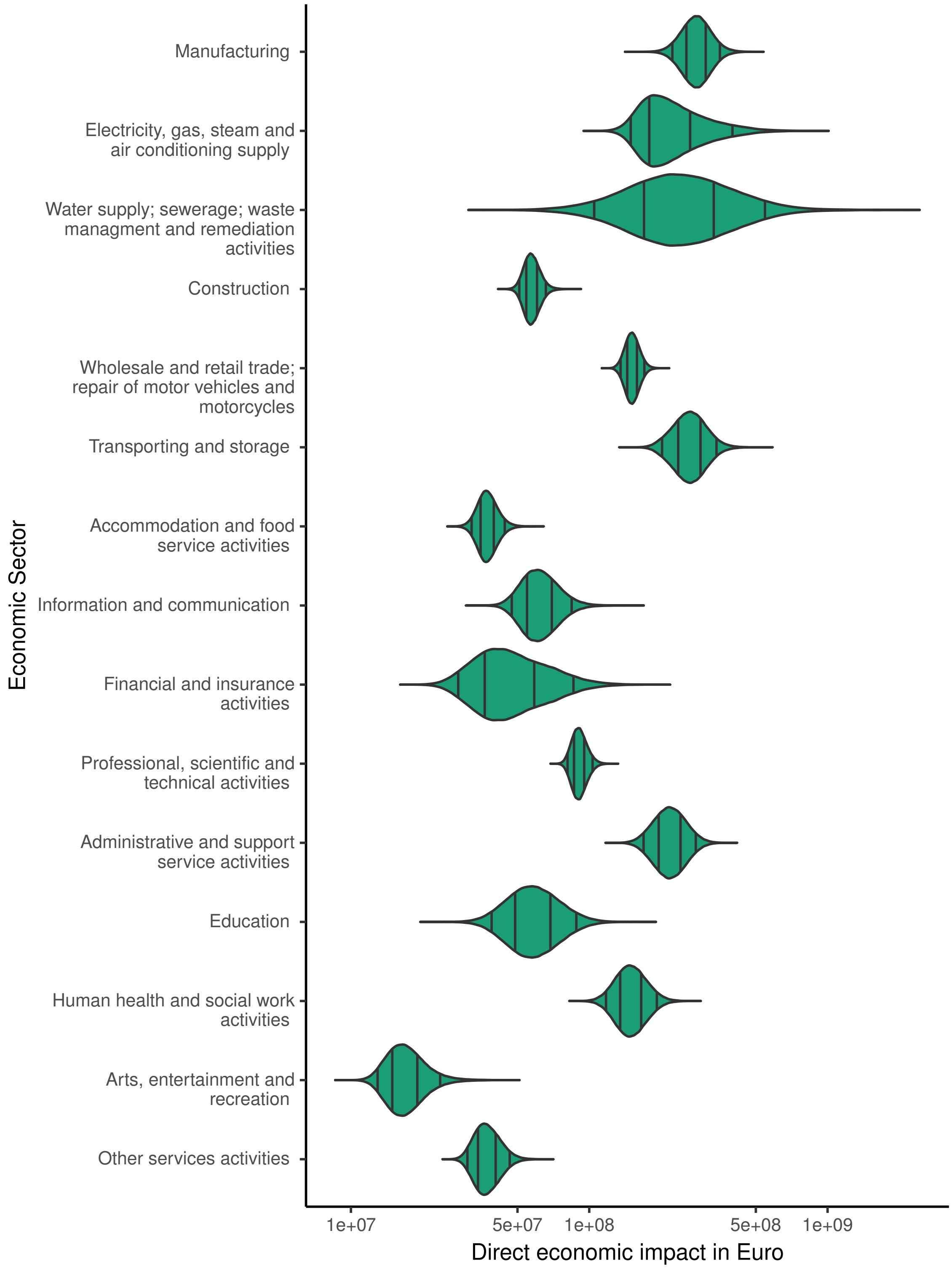

Figure 4.3: *Distributions of estimated direct economic impacts per economic sector. The black lines indicate the 50 % and 90 % intervals.*

4.3.3 Indirect economic impacts and ratio between indirect and direct impacts

The distributions of the estimated indirect impacts vary correspondingly to the direct impacts (Figure 4.4). The distribution locations of the sectors Mining and qarrying, Arts, entertainment and recreation, and other service activities show the lowest indirect economic impacts, while Manufacturing shows by far the highest impact. Manufacturing companies are often particularly prone to indirect impacts due to their many dependencies on e.g. input factors (such as materials needed for production) or the supply chain (Hiete & Merz, 2009; Haraguchi & Lall, 2015). One example is reported during a major flood event in 2000 in Tokai, Japan, where many production processes in companies not directly hit by the flood were stopped due to disturbances in the supply chain and infrastructure damage(Yang *et al.*, 2016). Hence, the high indirect economic impacts suffered by the sector Manufacturing seem plausible. The low indirect impacts suffered by the sector Arts, entertainment and recreation can also be explained by to their relative independence from supply chains and inputs of other sectors.

Figure 4.5 shows the ratio between indirect and direct impacts. Again, the distributions vary strongly between the sectors. The sectors Water supply; sewerage; waste management and remediation activities, Administrative and support service activities and Human health and social work activities show the lowest ratios in the range of 0.11 and 0.26 considering the 90 % intervals. Hence, direct economic impacts far exceed the indirect impacts on these sectors. The sector Manufacturing stands out as its complete distribution exceeds the value 1, indicating that this sector is mostly influenced by indirect impacts. Financial and insurance activities have a strong interrelation with other economic sectors and the economic growth (Pradhan *et al.*, 2017). Hence, although the direct economic impacts on this sector are rather moderate (Figure 4.3), the indirect impacts can be quite high explaining the rather high ratios (Figure 4.5). This variation in ratios between the economic sectors sheds doubt on the approach to use the direct impacts as proxy for indirect impacts. Depending on the sector, indirect economic impacts can be as large as or even larger than direct impacts, but also much smaller. These ratios should be event unspecific and transferable between regions with similar economic systems.

Figure 4.6 shows the distributions of the direct and indirect economic impacts as well as the ratio accumulated for Germany. The direct economic impacts of the flood event 2013 in Germany lie with a probability of 90 % between 1.5 and 2.1 billion Euro, while the indirect economic impacts lie between 1.1 and 1.6 billion Euro. The ratios for Germany range between 0.7 and 0.9 indicating that indirect impacts can almost be as high as direct impacts. This confirms the results of recent studies at the global scale, which observe direct and indirect economic impacts

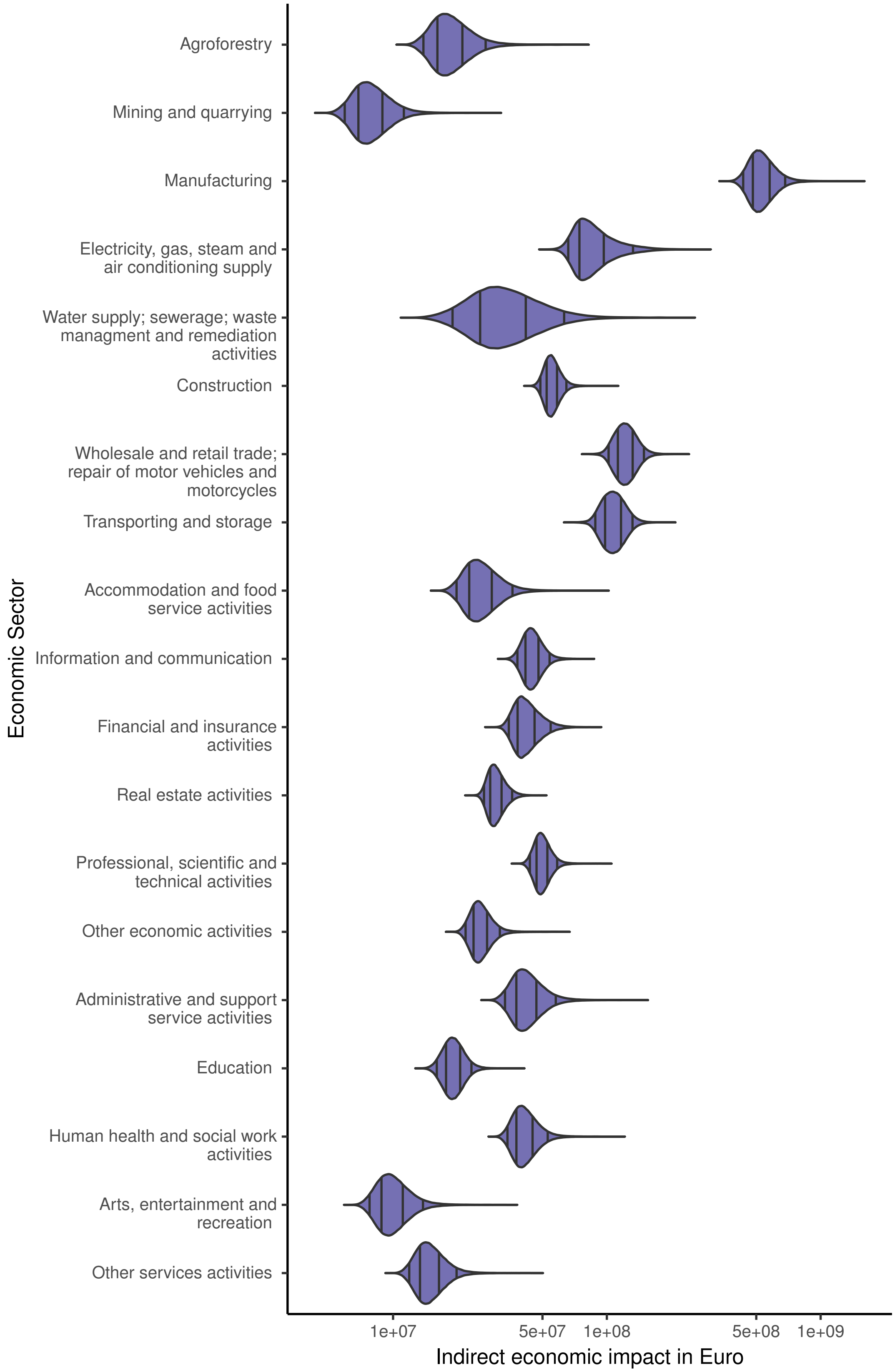

Figure 4.4: *Distributions of estimated indirect economic impacts per economic sector. The black lines indicate the 50 % and 90 % intervals.*

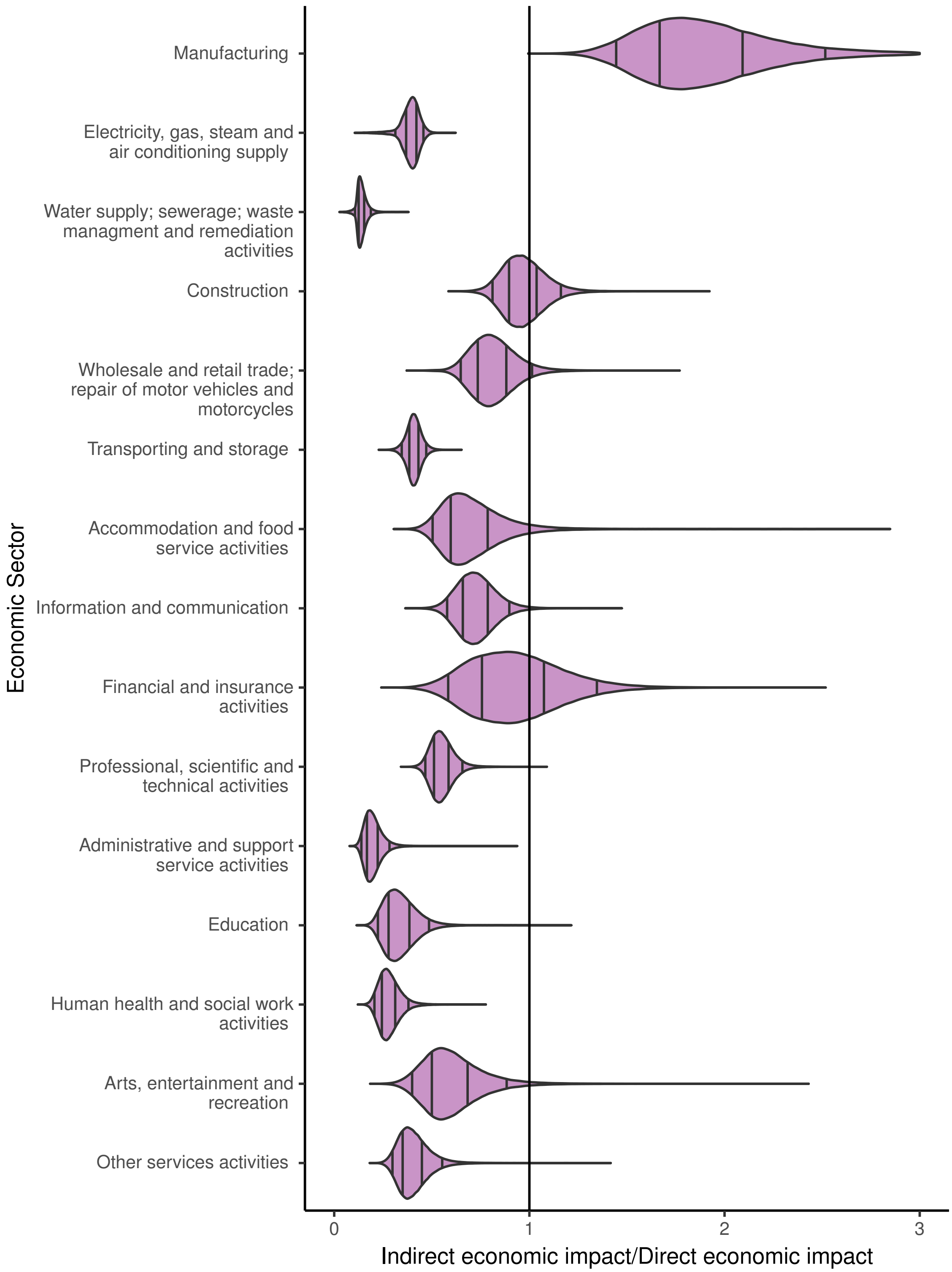

Figure 4.5: *Distributions of the ratio between indirect and direct estimated economic impacts per economic sector. The black lines indicate the 50 % and 90 % intervals.*

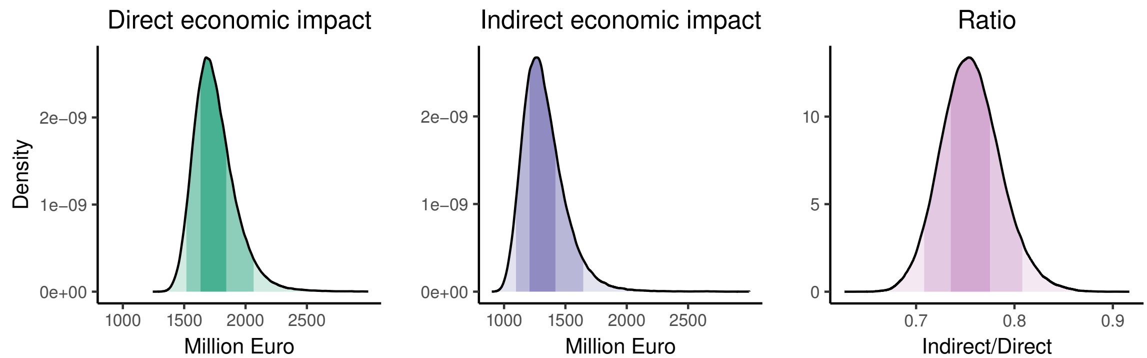

Figure 4.6: *Distributions of estimated direct economic impacts (green), estimated indirect economic impacts (purple) and the ratio (pink) of both for Germany. The different shades of the colours indicate the 50 % and 90 % intervals.*

of floods to be almost even (Koks, 2018; Willner *et al.*, 2018b). In addition, these findings also support the point made by Hallegatte (2008) that focusing on direct losses only, is insufficient for measuring disaster consequences.

4.4 Conclusion

This study proposes a new modeling procedure for the joint assessment of direct and indirect economic flood impacts under uncertainties. For the first time an object-based estimation of direct economic flood impacts at the national level is successfully conducted. The resulting estimations are plausible compared to reported damage values. Hence, data sets containing individual buildings are suitable for the seamless estimation of direct economic flood impact at large spatial scales.

Within the same modeling procedure the direct economic impacts are linked to a supply-side IO model for estimating the indirect economic impacts. The ratio between indirect and direct economic impacts reveals to which kind of impact the economic sectors are more prone to. Large differences in this ratio between the economic sectors are identified. This indicates that the application of a single factor to direct economic impacts as a proxy for the indirect impacts is inappropriate. Furthermore, direct and indirect economic flood impacts are found to be almost equal, highlighting the importance to include indirect economic impacts in flood risk assessments and management. The proposed procedure can be applied at any spatial scale, although a limiting factor might be the data availability for IO models. Its probabilistic nature also allows its use for projections of the consequences of future flood events, since assumptions about possible future developments of e.g. the economy can be expressed by probability distributions. Therefore, uncertainties associated with the assumptions are captured.

Future research should investigate the uncertainty associated with the estimation of indirect economic impacts. CGE models could be integrated into the proposed procedure to analyze the long-term flood impacts. Furthermore, validating especially indirect economic impacts is an urgent challenge.

5 Discussion, Outlook and Synthesis

5.1 Discussion

The main objective of this thesis was to improve flood damage estimations and the representation and propagation of their uncertainties across all spatial scales. The main achievement of this thesis is the development and application of a novel method. This method enables hydro-meteorological damage estimation at seamless spatial scales allowing for a consistent risk assessment with an inherent and comprehensive uncertainty quantification. The basis of the single features have already partly appeared in former studies, such as the use of a detailed exposure map (Chen *et al.*, 2016), the object-based damage modeling approach for larger scales (Huttenlau *et al.*, 2010; Prahl *et al.*, 2016) or attempts to include uncertainties associated with SDFs (Saint-Geours *et al.*, 2015). The studies presented in this thesis are the first which combine these features into one approach and applies it from the micro, up to the macro scale.

The method facilitates the explanation and overcoming of weaknesses in state-of-the-art models describing the damage processes. It enables advances in post-event analysis and future risk assessments across all spatial scales and also opens new directions for research on the improvement of the estimations. All of these aspects are discussed in the following Subchapters in view of the overarching **research question**:

> How can the reliability of hazard damage estimations and risk assessments be improved, represented and propagated consistently across spatial scales?

5.1.1 Description of the damage process

Chapter 2 and 3 contribute to the improvement of the description of the vulnerability. In Chapter 2, tree-based models are built to estimate the flood damage incurred by companies and for the identification of important damage-influencing variables. Overall, this study found that flood damage models with higher individuality, the inclusion of specific information and an increase in training data improves the reliability of flood damage estimations. Furthermore, the method developed in Chapter 3 facilitates the explanation of the low accuracies of state-of-the-art mirco-scale damage models.

Damage-influencing variables

A reliable description of the damage process requires knowledge about the influencing variables. The main damage-influencing variable identified is the water level. In this respect, the results are in line with comparable research results from studies aiming to identify damage-influencing variables of households (Merz *et al.*, 2013; Spekkers *et al.*, 2014; Thieken *et al.*, 2005). The water level is dominant as a damage-influencing variable for almost all company sectors and assets. Other variables, such as the spatial situation of the company or precaution measures undertaken, are influential as well (Figure 2.5). This supports the use of multi-variable flood damage models, which are able to consider several explanatory variables for their predictions (Merz *et al.*, 2013; Schröter *et al.*, 2014; Vogel *et al.*, 2014; Wagenaar *et al.*, 2017).

Different damage-influencing variables are identified for the various company sectors and assets, indicating different damage processes (Figure 2.5). Hence, a single damage model estimating direct flood damage to different kinds of companies and assets is not appropriate. Instead, different damage models should be developed aiming to describe the various damage processes. These results justify the sector-specific approaches undertaken in many flood damage models (Penning-Rowsell *et al.*, 2005; Scawthorn *et al.*, 2006; Seifert *et al.*, 2010a; Hasanzadeh Nafari *et al.*, 2016b) and underlines the importance of taking the differences of damage processes with respect to companies' assets into account.

Damage processes and their description are influenced by many parameters, which might not necessarily be obviously recognizable. The identification of the damage-influencing variables supports the development of damage models and facilitates the planning of further data collections. Furthermore, it contributes to the understanding of the damage process and therefore helps to gain reliability of flood damage estimations.

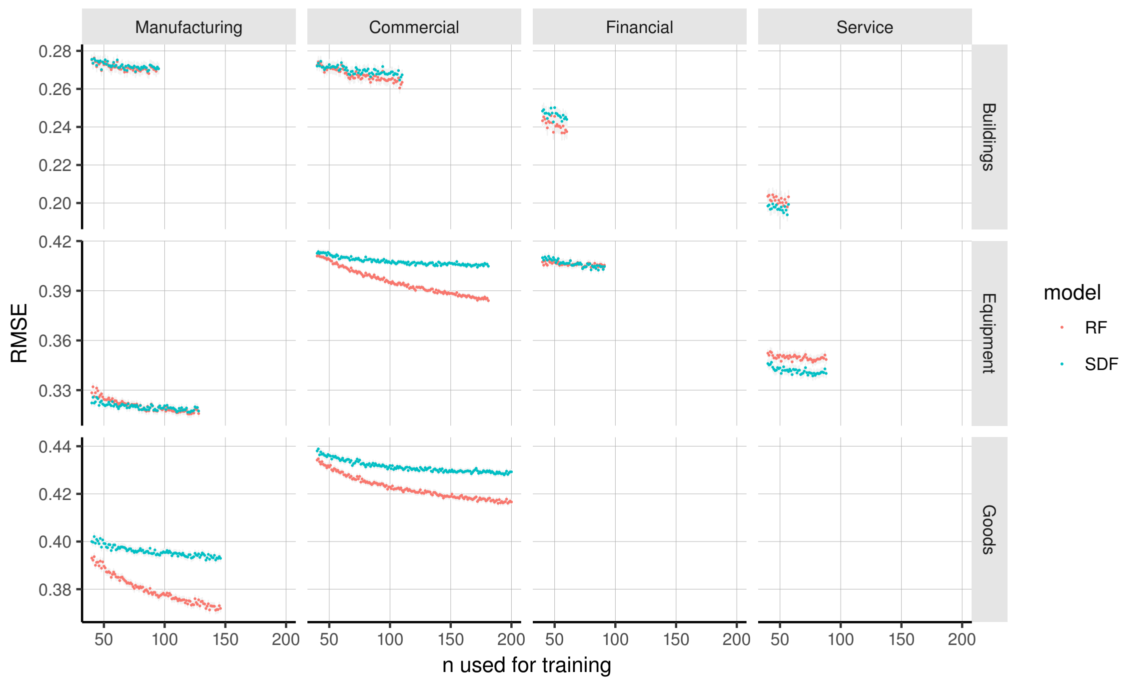

Figure 5.1: *Mean RMSE of estimates of RFs (red) and SDFs (blue) trained with differently sized data sets with a 95% confidence interval (light gray).*

Model performance

The quantification of the performance of models trained with differently sized data sets shows that the prediction accuracies of the tree-based models improve slightly, but significantly, with an increasing amount of training data (Figure 2.7). However, a sector-specific consideration of flood damage turned out to be more effective than a sole increase in quantity of the training data sets. In addition, a comparison of model performances of SDFs and RFs indicates that machine learning algorithms like RFs tend to profit more from additional data (Figure 5.1). Sector and asset-specific machine learning models trained with data sets containing more than 50 data points are most promising to improve the reliability of micro-scale flood damage estimates.

In general all models show large errors in the validation (Figures 2.6, 2.7 and 5.1). These large errors are observed in almost all studies validating flood damage models for both residential and commercial objects at the micro-scale (Jongman *et al.*, 2012b; Hasanzadeh Nafari *et al.*, 2016b; Schröter *et al.*, 2014; Seifert *et al.*, 2010a; Thieken *et al.*, 2008; Wagenaar *et al.*, 2018). Compared to these large errors, the improvements made possible with the use of sector-specific information,

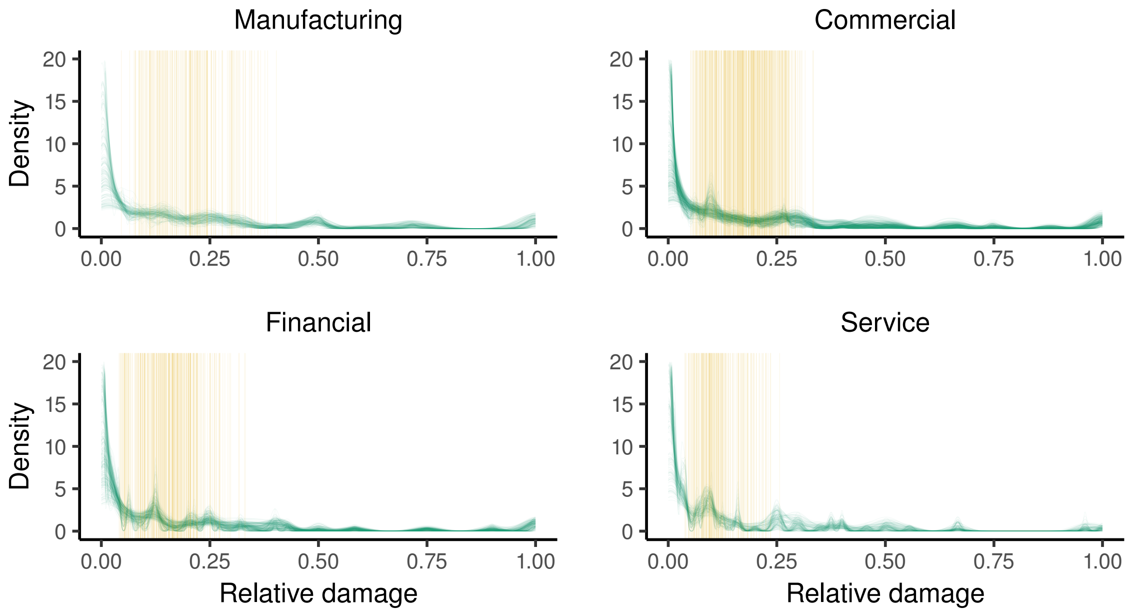

Figure 5.2: Distributions of relative damage estimates (green; RF distribution) and point estimations (yellow; RF point) for many different companies of the respective economic sector groups.

additional data sets and multi-variable models, are rather low. Consequently, the following question arises.

Why are state-of-the-art micro-scale model performances so low?

The vast majority of state-of-the-art damage models, both single-variable models such as SDFs (Scawthorn *et al.*, 2006; Grigg & Helweg, 1975; Emschergenossenschaft & Hydrotec, 2004) as well as multi-variable models such as tree-based models (Carisi *et al.*, 2018; Merz *et al.*, 2013; Schröter *et al.*, 2014; Sieg *et al.*, 2017; Wagenaar *et al.*, 2017), make use of point estimations to predict flood damage. Using only point estimators, these approaches are inherently unable to reflect uncertainties associated with the description of the damage process. The most commonly used point estimator is the mean which, assumes normally distributed values.

In general, it was observed that flood damage does not necessarily follow a normal distribution (variable rloss in Figure 2.3), but can rather be modeled by a log-normal (Merz *et al.*, 2004) or beta distribution (Egorova *et al.*, 2008). Consequently, the assessment of the distributions in comparison to point estimates shows that the point estimates, which are typically mean values in the case of classical state-of-the-art approaches, and thus are unlikely estimates for the flood damage (Figures 3.2 and 5.2). Averaging observed damage values, whose empirical distributions do not follow a normal distribution to estimate the damage leads to over- or underestimations resulting in high error rates (Figures 2.6 and 5.1). Resultantly the low performance of state-of-the-art micro-scale damage models is based on false assumptions and inappropriate estimators trying to describe a highly variable damage process.

Considering damage estimations at larger scales and therefore for a higher number of objects, the empirical distributions of observed damage values are more likely going to fit to a normal distribution (Figure 3.2). This phenomenon can be explained by the central limit theorem. Briefly described this theorem states that the sum of a large number of independent identically distributed random variables converges to a normal distribution, although the individual random variables might follow any kind of distribution. Thus, mean estimators might be further used at meso- and macro-scales, yet, with the disadvantage of a lacking uncertainty quantification of the vulnerability.

Distributions can be assessed aiming to capture the variability of the process more reliably. Egorova *et al.* (2008), for example, use beta distributions whose mean values are located on a SDF to capture the uncertainty of the prediction. Another possibility to make use of distributions is the application of bayesian models (Rözer *et al.*, 2018; Vogel *et al.*, 2014). In this case a certain distribution, which might result from prior knowledge, is used to capture the variability of the damage process. Or, as performed in this thesis, empirical distributions of damage estimates can be derived from RFs following the algorithm of Meinshausen (2006).

The use of distributions of damage estimates as actual results enables a more realistic and plausible estimation on the possible range of damage for a particular object or within a region (Figures 3.4, 3.A.1 and 4.2). This facilitates the communication of the reliability of the results and prevents a false sense of security towards the estimations.

5.1.2 Consistency of spatial scales

One aspect of the Chapters 3 and 4 is how the proposed method dissolves differences between risk assessments at different spatial scales. The basic mechanism is explained and applied to the meso-scale in Chapter 3, while a large-scale application is conducted in Chapter 4. For the latter application, affected objects need to be identified based on an extended version of openstreetmap.org (OSM) and a water mask. Despite the successful application of the method at the macro-scale, some limitations are found for the identification of affected objects with the OSM data sets and the water masks at the micro and meso-scale.

Spatial scales

The approach of object-based damage estimation in conjunction with global exposure data sets (Pittore *et al.*, 2017) facilitates the handling of consistent spatial scales. Former approaches exhibit the problem of developing and testing damage models at the object level, but applying these models to e.g. land use data to estimate the damage at larger scales (Jongman *et al.*, 2012a; Schwierz *et al.*, 2010). Hence, different kinds of data sets are used for the development and the actual application. These jumps between the scales and data sets can be a source for inaccuracies, in addition to the inconsistencies in the used land use data itself (de Moel *et al.*, 2015; Prahl *et al.*, 2016). The proposed object-based method in this thesis enables the use of the same input data sets and the same modeling approaches no matter on which spatial scale the damage is estimated.

Large-scale application

An important input parameter for the application of the developed method is the number of objects affected by a natural hazard in a region of interest as part of the exposure. In Chapter 3 the numbers of affected objects were taken from the damage records of the SAB. This kind of data is typically not available, especially at larger spatial scales such as countries. Typically input data sets such as land use maps (Gerl *et al.*, 2016) or the GDP of a country (Ward *et al.*, 2013) are used for large-scale applications. These input data sets are not applicable to an object-based method, additionally to their inherent inaccuracies. Thus Chapter 4 demonstrates the use of data sets containing individual buildings to obtain the number of companies affected by the flood in 2013 in Germany. In this application, the OSM data sets are overlapped with a water mask obtained by JBA to identify affected companies. This is the first large-scale application of an object-based approach that allows for a seamless estimation of flood damage from the object level to the national level. The application is not limited to the national scale. Theoretically,

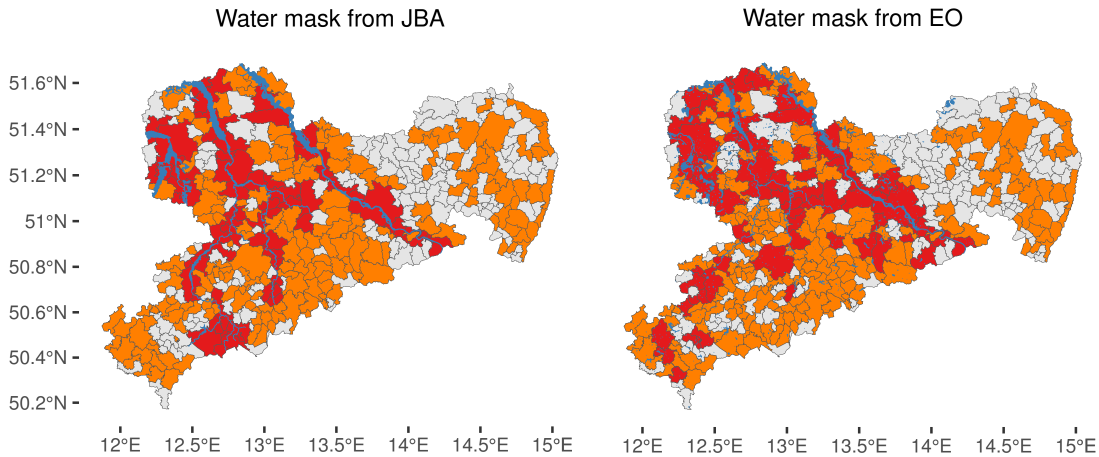

Figure 5.3: *Maps of Saxony with the water masks obtained by JBA and EO. Municipalities in orange are recorded by the SAB only, municipalities in red are recorded by the SAB and are identified by the overlap of the water masks and the OSM data sets.*

the spatial scale could be further enlarged to the continental or even the global scale.

The large-scale application at the federal state level shows that the identified numbers of affected companies as well as the damage estimates are comparable to the reported numbers (Figure 4.2). Compared to large-scale flood damage estimations with state-of-the-art approaches of recent studies (Ward *et al.*, 2013; Winsemius *et al.*, 2013; Alfieri *et al.*, 2016b), the proposed method performs just as well or even better. In addition, these results are in the form of distributions of flood damage estimates and thus reflect the uncertainties associated with the damage estimation.

Limitations at the meso-scale

Although the identification of the objects with the OSM data sets and the water mask works reliably from the meso-scale upwards (Figure 4.2), a more detailed look at smaller scales reveals that the identification of affected objects at the municipal level does not yet work as reliably.

Figure 5.3 shows a map of affected municipalities of Saxony reported by the SAB and identified by the overlap of the OSM data and water mask obtained by JBA on the left side with the water mask obtained by Earth Observations (EO) on the right hand side. The water mask from JBA was generated by hydrological and hydraulic models, while the other water mask originates from different sources of EO data. The maps show that the number of identified municipalities differs

Table 5.1: *Numbers of companies affected identified by the overlap of the OSM data sets and the water masks obtained by JBA and EO, respectively, and numbers of companies affected taken from the records of the SAB.*

Municipality/Federal State	SAB	OSM-JBA	OSM-EO
Döbeln	195	60	1
Grimma	139	60	9
Dresden	167	312	252
Leipzig	7	160	28
Saxony	2451	2548	877

strongly between the reported numbers from the SAB (260 municipalities affected) and the number resulting from the overlap of the water masks and the OSM data (JBA 82 municipalities affected; EO 77 municipalities affected). Different municipalities are identified by the two water masks, illustrating the spatial differences between the water masks, although the numbers of municipalities are quite similar (Figure 5.3).

Not only do the number of municipalities differ strongly, but also the number of objects affected within the municipalities show high differences. Table 5.1 shows the number of identified objects in selected municipalities. For the case of the city of Leipzig, the number obtained with the water mask of JBA differs by a factor of more than 20 to the number reported in the SAB data. Consequently, the estimation of the direct damage in Leipzig would also differ strongly resulting in a huge overestimation of the damage compared to the SAB records. The number of objects identified with the water mask of the EO in Leipzig is much closer to the reported objects. However, in other cases as e.g. in Döbeln the number of objects are vastly underestimated (by a factor of 195), thus, also the damage estimation would come up with much lower values. Huge differences between damage estimations based on different water masks would be obtained. The high errors in meso-scale damage modeling of former studies (Jongman *et al.*, 2012a; Kreibich *et al.*, 2016; Seifert *et al.*, 2010a) could also be explained by the difficulties in identifying the affected areas and objects due to the water masks, in addition to the inconsistencies in land use data detected by Jongman *et al.* (2012a) and the general uncertainties present in damage models.

Areas in Saxony, which are not identified by any of the water masks but are reported in the SAB data such as in the eastern or the central southern part of Saxony are a bit striking (Figure 5.3). These parts could have been affected by small scale flood events, such as ground water flooding or brief flood events, which are not detectable with the methods used for the derivation of the water masks.

The water mask produced by JBA mainly focuses on large rivers and might therefore not cover brief flood events that are not directly linked to a river. Consequently, it can be suspected that the JBA water mask overestimates the number of affected objects in the municipalities, but underestimates the number of affected municipalities in the federal state, which results in a good estimate for the federal state as a whole. This could be a coincidence, however, for seven other federal states it seemed to work almost equally well in respect to the estimated damage (Figure 4.2). Consequently, the identification of objects at larger scales with this water mask works reliably compared to reported damage values.

With regard to the EO data sets it is possible that areas which were only flooded for a short time were simply not flooded during the time the images were taken. Moreover, EO data sets also have inherent uncertainties, depending on the sensors' spatial resolution, affecting the delineation of inundated areas (Stephens *et al.*, 2012). However, EO-based approaches are generally capable for flood forecasting (García-Pintado *et al.*, 2015) and water masks derived from EO with an appropriate spatial resolution can be quite accurate, even on smaller scales (Gstaiger *et al.*, 2012). Hence, inaccuracies of the water mask derived by EO might alone not explain the huge differences between the objects reported in the SAB and objects identified by the EO data sets.

Yet, validation of flood damage estimates, and therefore also the identification of affected objects, is generally a difficult task due to data limitations - even if data is available, there might be uncertainties associated with it (Merz *et al.*, 2010). Consequently, inaccuracies within the SAB data sets cannot be excluded, although they seem to be unlikely.

The discussion above illustrates the huge impact of the choice and availability of hazard maps on the actual estimation of the economic impacts. The variations of identified objects would directly translate into varying damage estimates indicating the necessity of the inclusion of uncertainties associated with all components of flood damage estimation. Especially, since it was shown that it is possible to calculate a valid distribution of damage estimates, if the number of affected objects in a region is known (Figures 3.3, 3.4 and 3.A.1).

5.1.3 Representation of uncertainties

An additional aspect which is addressed in Chapter 3 and 4 is the representation and propagation of uncertainties. The method developed in Chapter 3 introduces probability distributions to capture uncertainties associated with hazard, exposure and vulnerability at all spatial scales. In addition to the propagation of uncertainties across spatial scales, Chapter 4 presents a modeling procedure that enables the propagation of uncertainties in the form of distributions of damage estimates from one model to another. Furthermore, the influence of the data sets used to describe the hazard, exposure and vulnerability on the resulting damage estimates is discussed.

Uncertainty and future projections

The need for a representation of uncertainties associated with flood damage estimations was already identified some years ago (Kreibich *et al.*, 2014; Ward *et al.*, 2015). However, recent advances are still lacking on this aspect.

The developed method is able to increase the reliability of flood damage estimations by showing the uncertainties associated with the estimations. This facilitates not only post-event assessments, but also future risk assessments. Uncertainties due to assumptions made, as well as unavailable or inaccurate data, can therefore be shown in the projections of the future risk assessments. As this is one of the main weaknesses of current projection studies, the proposed method contributes to a more honest communication about the validity and plausibility of current modeling approaches (Alfieri *et al.*, 2016a; Rojas *et al.*, 2013; Ward *et al.*, 2017; Winsemius *et al.*, 2013, 2016; Willner *et al.*, 2018b). For example, Dottori *et al.* (2018) use an ensemble for river flow projections to account for the hydrological uncertainties missing in former studies. However, the damage estimates are modeled with SDFs on the basis of GDPs per country and uncertainties associated with these descriptions of exposure and vulnerability are not considered. The lack of communication of these uncertainties might result in misleading conclusions and a false certainty about the results of the projections. The contributions of the proposed method to the communication of the uncertainties can be transferred to any spatial scale as a result of the seamless spatial scaling feature.

Uncertainty propagation

This scaling enables the propagation of damage estimates and the associated uncertainties between spatial scales. However, the propagation of uncertainty between different models requires an additional approach.

Thus far, only a few studies have attempted to link of direct and indirect damage estimations (Jonkman *et al.*, 2008; Koks *et al.*, 2015). SDFs are used typically for the estimation of the direct economic impacts and uncertainties associated with the computation are usually not considered. Chapter 4 proposes an approach, which links both estimations while considering uncertainties (Figure 4.1). Where previous studies only give point estimates (Carrera *et al.*, 2015; Jonkman *et al.*, 2008; Koks *et al.*, 2015), this procedure links the estimations of direct and indirect economic impacts resulting in probability distributions of the economic impact. The application shows that the propagation of uncertainties through different models can be visualized independently of the spatial scales, if the required data sets to derive the indirect models are available. Thus, the results of the modeling procedure facilitate the representation and communication of the reliability of estimated total economic impacts. In addition to the considered uncertainties associated with the estimation of the direct economic impacts, uncertainties associated with indirect estimations could also be included (Temurshoev, 2017).

The influence of hazard, exposure and vulnerability uncertainty

The quantification of uncertainties also facilitates the improvement of the methods' reliability by identifying the components that contribute most to the uncertainty of the results. In general, it can be distinguished between two types of uncertainty in flood risk assessments: the aleatory and the epistemic uncertainty (Merz & Thieken, 2009). Aleatory uncertainty describes processes that are inherently variable and might show a stochastic or random behavior. Epistemic uncertainty originates from an incomplete knowledge of the underlying system and can be reduced by including additional information and an improved understanding. The attribution of these kinds of uncertainty to different components of risk is a recurring subject of (almost philosophical) debates. Here, this topic is discussed against the background of the state-of-the-art knowledge and not of the knowledge that could theoretically be available in the future. The aim is to discuss, which uncertainties can most likely be reduced (epistemic) and which cannot (aleatory).

From the findings of this work it can be concluded that the uncertainty associated with vulnerability can be characterized as mostly aleatory. Although, the accuracy of damage models could be increased to a certain extent, the remaining errors were still high (Figures 2.6 and 2.7). In addition, different models did not show profound differences with regard to the model performances (Figures 5.1), which is in line with recent studies (Schröter *et al.*, 2014; Wagenaar *et al.*, 2017). Considering probability distributions of possible damage estimates for individual companies, it can be suspected that the underlying damage process, which is described by the vulnerability is, to a large extent, stochastic (Figure 5.2). This is supported by considering a practical example: assuming, a window in the basement of a store, which at the same time serves as storage room, is left open during a flood event and consequently the flood water causes huge damage. The same store would have suffered no damage if the window would have been closed. From a modeling point of view it is almost impossible to know about the status of the openness of the window. Even by including more data, these details in the damage process will most likely remain as an stochastic element. However, this stochastic behavior can be modeled by probability distributions. Consequently, a representation of uncertainties reflecting the stochasticity associated with the damage process should be included, as a reliable deterministic description of these processes seems unlikely.

In contrast, uncertainties associated with the exposure can be described as mostly epistemic. The exposure data sets specify, in conjunction with the hazard maps, the number of objects (variable k in Figure 3.1 F) affected by a natural hazard (Figure 5.3 and Table 5.1). Therefore, these data sets also strongly determine the order of magnitude of the estimated damage. In case the number of objects affected is known, the damage estimations are quite reliable (Figure 3.A.1). Asset values of exposed objects can be estimated or are available in many industrial countries and uncertainties associated with these (estimated) values can again be represented by distributions. Thus, an improved identification of affected objects will also contribute to more reliable damage estimates. Information about single objects has been gathered extensively during the last years, including data sets such as openstreetmap.org (Pittore *et al.*, 2017; Wieland & Pittore, 2017). The required data has already been collected, yet it is mostly not used in risk assessments. Consequently, on the part of exposure, there is a large capacity for the improvement of damage estimations and risk assessments, if the information is incorporated appropriately.

However, information on the hazard is also required for the identification of affected objects. The uncertainties associated with the hazard have not been investigated extensively in this thesis. Yet, based on the observations made by comparing two water masks, it is clear that hazard maps are both highly influential and uncertain (Figure 5.3). In order to include the uncertainty associated with the hazard, ensembles of hydrological and hydraulic models can be used to obtain a range of water masks (Hirabayashi *et al.*, 2013; Velázquez *et al.*, 2013). Alternatively, in case model outputs are not available, distributions of the water level, and even of affected objects, could be assumed and used for the estimation of potential damage. Depending on the assumptions, these estimates would vary widely, but could at least give a very first estimate of the order of magnitude of the damage.

These findings partially contradict to the results of former research. A study by de Moel & Aerts (2011) investigates the effect of uncertainty in land use (exposure), damage models (vulnerability) and inundation depth (hazard) on the model results. They found that value of elements at risk and the depth-damage curves contribute mostly to the overall uncertainty. A study of Apel *et al.* (2009) claims that the choice of the damage model has a much larger impact on the damage estimations than the choice of the flood model. In this thesis, the asset value, as part of the exposure, is also identified as an important driver, while the choice of the flood damage models is considered less important. This seems logical, as the identification of affected objects is mainly driven by the hazard and exposure. At the same time, the number of affected objects determines the total values affected and therefore influences the estimated damage strongly. Consequently, it is to be expected that hazard and exposure are highly influential.

Hence, the uncertainty associated with vulnerability can only hardly be reduced by the inclusion of additional data. Also with the use of different models an substantial improvement of the estimates' accuracies could not be observed. In contrast, the uncertainty associated with exposure, as present in recent damage and risk assessments, can be decreased by the inclusion of newly available exposure data sets containing individual buildings. Yet, the identification of affected objects is still highly inaccurate, especially at smaller scales due to uncertainties associated with the hazard. Therefore, it seems to be rewarding to actively include exposure and hazard data including their uncertainties, additionally to the improvement of methods describing the vulnerability.

5.2 Outlook

On the basis of the previous discussion, there is diverse research that can be carried out in the future. The application of the developed object-based method could be expanded to additional hydro-meteorological hazards such as e.g. windstorms (Prahl *et al.*, 2015; Pardowitz *et al.*, 2016), pluvial floods (Rözer *et al.*, 2016), flash floods (Laudan *et al.*, 2017; Öztürk *et al.*, 2018) or even glacial lake outburst floods (Veh *et al.*, 2018). Additional assets from other sectors such as private households or infrastructure, which are also detectable with the data sets containing individual buildings, could be considered in the risk assessments (Pittore *et al.*, 2017). Another facet, which is so far missing with regard to economic impacts of companies is the business interruption of directly affected companies due to a flood event (Sultana *et al.*, 2018).

In the spatial domain, the applications could be widened to larger extents e.g. the European scale, as it is done with land use based approaches (Rojas *et al.*, 2013; Schwierz *et al.*, 2010). In the temporal domain, the method could be applied to future projections. The probabilistic feature of the method facilitates the inclusion of the assumptions made for the projections in form of distributions. Thereby the projections would contain uncertainties associated with the assumptions concerning all three components of risk hazard, exposure and vulnerability. The contribution of each of these components to the overall uncertainty could be assessed by an systematic sensitivity analysis. It could be used as a starting point for the reduction of the uncertainties.

Furthermore, the method itself could be developed further by the inclusion of additional models such as bayesian models (Rözer *et al.*, 2018) for the estimation of direct economic impacts as well as more sophisticated models for the estimation of short and long-term indirect economic impacts as the adaptive regional IO model (Hallegatte, 2008) or CGE models (Carrera *et al.*, 2015; Koks *et al.*, 2016). Another technical aspect is the improvement of identification of affected objects. At the moment every object intersecting with the water mask is counted as an affected object. Improvements could focus on integrating the area of an object overlapped with the flood mask in the damage calculations.

5.3 Synthesis

This thesis demonstrates how the reliability of flood damage estimates can be improved, represented and propagated across spatial scales.

Classical attempts to improve the reliability of current micro-scale damage estimations do not lead to fundamentally increased prediction accuracies. Point estimators, such as the mean, are incapable of representing the highly variable damage processes, since the underlying distributions of damage values do not follow a normal distribution. Instead, methods giving distributions of possible damage estimates should be preferred, as they comprise more information about the reliability.

The use of object-based damage models across all spatial scales prevents the introduction of uncertainties through inconsistent state-of-the-art models and inaccurate exposure data sets. Newly available data sets containing individual buildings overcome these inaccuracies and facilitate object-based approaches. Probability distributions can be used to represent missing information about object characteristics. The combination of the object-based approach and the use of distributions capturing uncertainties, results in increased accuracies of the estimated direct economic impacts.

A subsequent propagation of the resulting distributions into models that estimate indirect economic impacts allows for the inclusion of uncertainties in the assessment of economic systems as a whole. This is an important step towards the analysis of the estimated total economic flood impact and its reliability.

The identification of objects affected by a given flood event requires maps depicting flooded areas. These can show wide disparities depending on the data sets and methods used for their derivation. The disparities have a major influence on the identification of affected objects, which in turn have a high influence on the damage estimates' order of magnitude. Consequently, the consideration of the hazards' variabilities is necessary for a reliable estimation of flood damage.

The influence on the estimates' reliability of hazard and exposure is much higher than the influence of the damage processes. Therefore, the focus should be placed on the inclusion of new data sets describing the hazard and exposure, as well as the representation of their reliability. The improvement of the description of damage processes is still needed, yet less promising in its potential role to substantially contribute to an increasing reliability of flood damage estimations.

In conclusion, I recommend the use of seamless object-based damage modeling approaches with an inherent uncertainty quantification to obtain more reliable flood damage estimations across spatial scales - now and in the future.

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