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Exploring the transferability of flood loss models across flood types

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Declaration of Originality

I, Guilherme Samprogna Mohor, hereby declare that the dissertation

„Exploring the transferability of flood loss models across flood types“

was developed and prepared by myself, by means of the stated sources and data, for the acquirement of the respective degree of Doctor of Engineering (Dr.-Ing.) at the University of Potsdam.

All passages taken verbatim or in the same spirit from published or unpublished writings are identified as such. Co-authors of respective chapters have been duly identified. Financil support for parts or the integrity of the dissertation have been duly identified.

This dissertation or similar has not been submitted to any other University for examination.

Potsdam, January 2022 Guilherme Samprogna Mohor

Far better an approximate answer to the right question, which is often vague, than an exact answer to the wrong question, which can always be made precise

John Tukey, 1962

To my mother.

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Abstract

The estimation of financial losses is an integral part of flood risk assessment. The application of existing flood loss models on locations or events different from the ones used to train the models has led to low performance, showing that characteristics of the flood damaging process have not been sufficiently well represented yet. To improve flood loss model transferability, I explore various model structures aiming at incorporating different (inland water) flood types and pathways. That is based on a large survey dataset of approximately 6000 flood-affected households which addresses several aspects of the flood event, not only the hazard characteristics but also information on the affected building, socioeconomic factors, the household's preparedness level, early warning, and impacts. Moreover, the dataset reports the coincidence of different flood pathways. Whilst flood types are a classification of flood events reflecting their generating process (e.g. fluvial, pluvial), flood pathways represent the route the water takes to reach the receptors (e.g. buildings). In this work, the following flood pathways are considered: levee breaches, river floods, surface water floods, and groundwater floods.

The coincidence of several hazard processes at the same time and place characterises a compound event. In fact, many flood events develop through several pathways, such as the ones addressed in the survey dataset used. Earlier loss models, although developed with one or multiple predictor variables, commonly use loss data from a single flood event which is attributed to a single flood type, disregarding specific flood pathways or the coincidence of multiple pathways. This gap is addressed by this thesis through the following research questions: 1. In which aspects do flood pathways of the same (compound inland) flood event differ? 2. How much do factors which contribute to the overall flood loss in a building differ in various settings, specifically across different flood pathways? 3. How well can Bayesian loss models learn from different settings? 4. Do compound, that is, coinciding flood pathways result in higher losses than a single pathway, and what does the outcome imply for future loss modelling?

Statistical analysis has found that households affected by different flood pathways also show, in general, differing characteristics of the affected building, preparedness, and early warning, besides the hazard characteristics. Forecasting and early warning capabilities and the preparedness of the population are dominated by the general flood type, but characteristics of the hazard at the object-level, the impacts, and the recovery are more related to specific flood pathways, indicating that risk communication and loss models could benefit from the inclusion of flood-pathway-specific information.

For the development of the loss model, several potentially relevant predictors are analysed: water depth, duration, velocity, contamination, early warning lead time, perceived knowledge about self-protection, warning information, warning source, gap between

warning and action, emergency measures, implementation of property-level precautionary measures (PLPMs), perceived efficacy of PLPMs, previous flood experience, awareness of flood risk, ownership, building type, number of flats, building quality, building value, house/flat area, building area, cellar, age, household size, number of children, number of elderly residents, income class, socioeconomic status, and insurance against floods. After a variable selection, descriptors of the hazard, building, and preparedness were deemed significant, namely: water depth, contamination, duration, velocity, building area, building quality, cellar, PLPMs, perceived efficacy of PLPMs, emergency measures, insurance, and previous flood experience. The inclusion of the indicators of preparedness is relevant, as they are rarely involved in loss datasets and in loss modelling, although previous studies have shown their potential in reducing losses. In addition, the linear model fit indicates that the explanatory factors are, in several cases, differently relevant across flood pathways.

Next, Bayesian multilevel models were trained, which intrinsically incorporate uncertainties and allow for partial pooling (i.e. different groups of data, such as households affected by different flood pathways, can learn from each other), increasing the statistical power of the model. A new variable selection was performed for this new model approach, reducing the number of predictors from twelve to seven variables but keeping factors of the hazard, building, and preparedness, namely: water depth, contamination, duration, building area, PLPMs, insurance, and previous flood experience. The new model was trained not only across flood pathways but also across regions of Germany, divided according to general socioeconomic factors and insurance policies, and across flood events. The distinction across regions and flood events did not improve loss modelling and led to a large overlap of regression coefficients, with no clear trend or pattern. The distinction of flood pathways showed credibly distinct regression coefficients, leading to a better understanding of flood loss modelling and indicating one potential reason why model transferability has been challenging.

Finally, new model structures were trained to include the possibility of compound inland floods (i.e. when multiple flood pathways coincide on the same affected asset). The dataset does not allow for verifying in which sequence the flood pathway waves occurred and predictor variables reflect only their mixed or combined outcome. Thus, two Bayesian models were trained: 1. a multi-membership model, a structure which learns the regression coefficients for multiple flood pathways at the same time, and 2. a multilevel model wherein the combination of coinciding flood pathways makes individual categories. The multi-membership model resulted in credibly different coefficients across flood pathways but did not improve model performance in comparison to the model assuming only a single dominant flood pathway. The model with combined categories signals an increase in impacts after compound floods, but due to the uncertainty in model coefficients and estimates, it is not possible to ascertain such an increase as credible. That is, with the current level of uncertainty in differentiating the flood pathways, the loss estimates are not credibly distinct from individual flood pathways.

To overcome the challenges faced, non-linear or mixed models could be explored in the future. Interactions, moderation, and mediation effects, as well as non-linear effects, should also be further studied. Loss data collection should regularly include preparedness indicators, and either data collection or hydraulic modelling should focus on the distinction of coinciding flood pathways, which could inform loss models and further improve estimates. Flood pathways show distinct (financial) impacts, and their inclusion in loss modelling proves relevant, for it helps in clarifying the different contribution of influencing factors to the final loss, improving understanding of the damaging process, and indicating future lines of research.

Zusammenfassung

Die Schätzung finanzieller Schäden ist ein wesentlicher Bestandteil der Hochwasserrisikoanalyse. Die Anwendung bestehender Hochwasserschadensmodelle auf anderen Orten oder Ereignisse als jene, die zur Kalibrierung der Modelle verwendet wurden, hat zu einer geringen Modellgüte geführt. Dies zeigt, dass die Merkmale des Hochwasserschadensprozesses in den Modellen noch nicht hinreichend repräsentiert sind. Um die Übertragbarkeit von Hochwasserschadensmodellen zu verbessern, habe ich verschiedene Modellstrukturen untersucht, die darauf abzielen, unterschiedliche Hochwassertypen und wirkungspfade einzubeziehen. Dies geschieht auf der Grundlage eines großen Datensatzes von ca. 6000 Fällen überschwemmungsgeschädigter Haushalte, der mehrere Aspekte des Hochwasserereignisses berücksichtigt. Diese sind nicht nur die Gefährdungsmerkmale, sondern auch Informationen über das betroffene Gebäude, sozioökonomische Faktoren, die Vorsorge des Haushalts, die Frühwarnung und die Auswirkungen. Darüber hinaus enthält der Datensatz Informationen über das Vorkommen verschiedener Hochwasserwirkungspfade. Im Gegensatz zu den Hochwassertypen, die eine Klassifizierung von Hochwasserereignissen darstellen und deren Entstehungsprozess widerspiegeln (z. B. Fluss- oder Regenhochwasser), repräsentieren die Hochwasserwirkungspfade den Weg, den das Wasser nimmt, um die Rezeptoren (z. B. die Gebäude) zu erreichen. In dieser Arbeit werden folgende Hochwasserwirkungspfade betrachtet: Deichbrüche, Flusshochwasser, Überflutung durch oberflächlich abfließendes Wasser und Grundwasserhochwasser. Das Zusammentreffen mehrerer Gefahrenprozesse zur selben Zeit und am selben Ort kennzeichnet ein Verbundereignis (*compound event*). Tatsächlich entwickeln sich viele Hochwasserereignisse über mehrere Wirkungspfade, z. B. die vorher erwähnten. Frühere Schadensmodelle, die zwar mit einer oder mehreren Prädiktorvariablen entwickelt wurden, verwenden in der Regel Schadensdaten eines einzelnen Hochwasserereignisses, das einem bestimmten Hochwassertyp zugeordnet wird. Spezifische Hochwasserwirkungspfade oder das Zusammentreffen mehrerer Wirkungspfade werden dabei vernachlässigt. An dieser Forschungslücke setzt die vorliegende Arbeit mit folgenden Forschungsfragen an: 1) Inwiefern unterscheiden sich die Hochwasserwirkungspfade desselben (zusammengesetzten) Hochwasserereignisses? 2) Inwieweit unterscheiden sich die Faktoren, die zum gesamten Hochwasserschaden an einem Gebäude beitragen, in verschiedenen Situationen, insbesondere bei verschiedenen Hochwasserwirkungspfaden? 3) Wie gut können Bayes'sche Schadensmodelle aus verschiedenen Situationen lernen? 4) Führen gemischte, d. h. mehrere zusammentreffende Hochwasserwirkungspfade, zu höheren Schäden als ein einzelner Pfad und was bedeuten die Ergebnisse für die künftige Schadensmodellierung?

Die statistische Analyse zeigt, dass Haushalte, die von verschiedenen Hochwasserwirkungspfaden betroffen sind, im Allgemeinen neben den Gefahrenmerkmalen auch unterschiedliche Eigenschaften des betroffenen Gebäudes sowie der Vorsorge und der Frühwar-

nung aufweisen. Die Variablen des Frühwarnsystems und die Vorsorge der Bevölkerung werden von dem allgemeinen Hochwassertyp dominiert, wohingegen die Merkmale der Gefahr auf Objektebene, die Auswirkungen und die Wiederherstellung von den spezifischeren Hochwasserwirkungspfaden dominiert. Dies deutet darauf hin, dass Risikokommunikation und Schadensmodelle von der Einbeziehung hochwasserwirkungspfad-spezifischer Informationen profitieren könnten.

Für die Entwicklung des Schadensmodells wurden mehrere potenziell relevante Prädiktoren analysiert: Wassertiefe, Dauer, Geschwindigkeit, Verschmutzung, Vorwarnzeit, wahrgenommenes Wissen über Selbstschutz, Warninformation, Warnquelle, Zeitspanne zwischen Warnung und Handlung, Notfallmaßnahmen, Umsetzung von Vorsorgemaßnahmen auf Grundstücksebene (PLPMs), wahrgenommene Wirksamkeit von PLPMs, frühere Hochwassererfahrungen, Bewusstsein für das Hochwasserrisiko, Eigentumsverhältnisse, Gebäudetyp, Anzahl der Wohnungen, Gebäudequalität, Gebäudewert, Haus-/Wohnungsfläche, Gebäudefläche, Keller, Alter der befragten Person, Haushaltsgröße, Anzahl der Kinder, Anzahl der älteren Menschen, monatliches Einkommen sowie sozioökonomischer Status und Versicherung gegen Hochwasser. Nach einer Variablenauswahl wurden folgende Deskriptoren der Gefahr, des Gebäudes und der Vorbereitung als signifikant eingestuft: Wassertiefe, Verschmutzung, Überflutungsdauer, Geschwindigkeit, Gebäudefläche, Gebäudequalität, Keller, PLPMs, wahrgenommene Wirksamkeit von PLPMs, Notfallmaßnahmen, Versicherung und frühere Hochwassererfahrung. Die Einbeziehung der letztgenannten Gruppe von Faktoren ist von Bedeutung, da Indikatoren für die Vorsorge nur selten in Schadensdatensätze und Schadensmodellierung integriert werden, obwohl frühere Studien gezeigt haben, dass sie zur Verringerung von Schäden beitragen können. Die lineare Modellanpassung zeigte, dass die erklärenden Faktoren in mehreren Fällen je nach Hochwasserpfad unterschiedlich relevant sind.

Als Nächstes wurden Bayes'sche Mehrebenenmodelle trainiert, die Unsicherheiten immanent einbeziehen und ein partielles Pooling ermöglichen. Das heißt, verschiedene Datengruppen (Haushalte, die von verschiedenen Hochwasserwirkungspfaden betroffen sind) können voneinander lernen, was die statistische Aussagekraft des Modells erhöht. Für diesen neuen Modellansatz wurde eine aktualisierte Variablenauswahl getroffen, bei der die Anzahl der Prädiktoren von zwölf auf sieben reduziert wurde, aber Faktoren der Gefahr, des Gebäudes und der Vorbereitung beibehalten wurden. Diese sind Wassertiefe, Verschmutzung, Dauer, Gebäudefläche, PLPMs, Versicherung und frühere Hochwassererfahrung. Das neue Modell wurde nicht nur über Hochwasserwirkungspfade, sondern auch über Regionen in Deutschland – unterteilt nach allgemeinen sozioökonomischen Faktoren und Versicherungspolicen – sowie über Hochwasserereignisse trainiert. Die Unterscheidung nach Regionen und Hochwasserereignissen verbesserte die Schadensmodellierung nicht und führte zu einer großen Überlappung der Regressionskoeffizienten ohne klaren

Trend oder eindeutiges Muster. Die Unterscheidung nach Hochwasserwirkungspfaden ergab glaubhaft unterschiedliche Regressionskoeffizienten, was zu einem besseren Verständnis der Modellierung von Hochwasserschäden führte und einen möglichen Grund für die schwierige Übertragbarkeit der Modelle auf andere Situationen darstellt.

Schließlich wurden neue Modellstrukturen trainiert, um die Möglichkeit gemischter (Binnen)überschwemmungen, d. h. das Zusammentreffen mehrerer Hochwasserwirkungspfade auf demselben Objekt, zu berücksichtigen. Anhand des Datensatzes lässt sich nicht überprüfen, in welcher Reihenfolge die Hochwasserpfadwellen auftraten, und die Prädiktorvariablen zeigen nur deren gemischtes oder kombiniertes Ergebnis. Daher wurden zwei Bayes'sche Modelle trainiert: 1) ein Multi-Membership-Modell als Struktur, die die Regressionskoeffizienten für mehrere Hochwasserwirkungspfade gleichzeitig lernt, und 2) ein Mehrebenenmodell, bei dem die Kombination zusammentreffender Hochwasserwirkungspfade einzelne Kategorien bildet. Ersteres führte zu glaubhaft unterschiedlichen Koeffizienten für die verschiedenen Hochwasserwirkungspfade, verbesserte aber nicht die Modellleistung im Vergleich zu dem Modell, das nur einen einzigen, dominanten Hochwasserpfad annimmt. Das Modell mit kombinierten Wirkungspfadkategorien deutet auf eine Zunahme der Auswirkungen nach gemischten Überschwemmungen hin. Aufgrund der Unsicherheit der Modellkoeffizienten und -schätzungen ist es jedoch nicht möglich, eine solche Zunahme als glaubwürdig plausibel zu bewerten. Das heißt, bei dem derzeitigen Grad an Unsicherheit hinsichtlich der Differenzierung der Hochwasserwirkungspfade sind die Schadensschätzungen nicht glaubwürdig von den einzelnen Hochwasserwirkungspfaden zu unterscheiden.

Zur Überwindung der bestehenden Probleme könnten nichtlineare oder gemischte Modelle untersucht werden. Zudem sollten Interaktionseffekte, Moderations- und Mediationseffekte sowie nichtlineare Effekte weiter erforscht werden. Bei der Schadensdatenerhebung sollten außerdem regelmäßig Indikatoren für die Vorsorge einbezogen werden, und entweder bei der Datenerhebung oder bei der hydraulischen Modellierung sollte der Schwerpunkt auf der Unterscheidung kombinierter Hochwasserwirkungspfade liegen, was die Schadensmodelle bereichern und die Schätzungen weiter verbessern könnte. Hochwasserwirkungspfade zeigen differente (finanzielle) Auswirkungen und ihre Einbeziehung in die Schadensmodellierung hat sich als relevant erwiesen, da sie dazu beitragen, den unterschiedlichen Beitrag der Einflussfaktoren zum endgültigen Schaden zu klären, das Verständnis des Schadensprozesses zu verbessern und künftige Forschungslinien aufzuzeigen.

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Abbreviations

AIC	Akaike Information Criterion
BMM	Bayesian Multilevel Model
BN	Bayesian Network
CATI	Computer-Aided Telephone Interviews
ELPD	Expected Log Pointwise Predictive Density
GDV	German Insurance Association [Gesamtverband der Deutschen Versicherungswirtschaft]
HDI	Highest Density Interval
LOO-CV	Leave-One-Out Cross-Validation
MB	Markov Blanket
MCM	Multi-Coloured Manual
MAE	Median Absolute Error
N_eff	Effective Sample Size
PLPM	Property-level Precautionary Measure
R-hat ($\hat{R}$)	Gelman–Rubin potential scale reduction factor
RMSE	Root Mean Squared Error
UNDRR	United Nations Office for Disaster Risk Reduction (formerly UNISDR)

Chapter 1

Introduction

1.1 Motivation

Within the last period of my doctoral studies, in mid-July 2021, strong flash floods hit parts of western Europe. This was the worst flooding event for Germany in number of flood fatalities since 1962, with more than 180 deaths in the country (Thieken, Kemter et al., 2021) and 39 more in Belgium (Dewals et al., 2021). The financial and economic losses have not been thoroughly verified and published yet, but €30 billion has been preliminarily allocated for the overall reconstruction (Bundesministerium des Innern und für Heimat and Bundesministerium der Finanzen, 2021). Financial losses of this order surpass the previously most damaging events of 2002 (€11.6 billion) and 2013 (between € 6 and 8 billion) (Thieken, Bessel et al., 2016), also making this the most damaging flood in Germany in decades.

Climate change projections, though uncertain and spatially varied, point towards an increase in heavy precipitation, which will also heighten flood risks, leading to stronger impacts in Europe (Kovats et al., 2014). Thus, managing or reducing disaster risk is a 'no regret' adaptation. Regardless of climate change, extreme events and disasters will surely continue to occur, as the World Meteorological Organization (WMO) stated in a press release (WMO, 2021) after the publication of the 'Atlas of Mortality and Economic Losses from Weather, Climate and Water Extremes (1970–2019)' (Douris & Kim, 2021). Floods are one of the most frequent, fatal, and economically damaging disasters triggered by natural hazards, being responsible for 44% of economic disaster losses in Europe in the 1970–2019 period, or 31% in the world (Douris & Kim, 2021). Therefore, they are the focus of this thesis.

1.2 Disaster Risk

The Sendai Framework for Disaster Risk Reduction 2015–2030 goal is to 'prevent new and reduce existing disaster risk through the implementation of integrated and inclusive economic, structural, legal, social, health, cultural, educational, environmental, technological, political and institutional measures that prevent and reduce hazard exposure and vulnerability to disaster, increase preparedness for response and recovery, and thus strengthen resilience' (UNISDR, 2015). To achieve that goal, the Framework establishes seven global targets, including the reduction of direct disaster economic loss, for which monitoring is needed. Loss documentation is, however, an irregular and unstandardised procedure (Downton & Pielke Jr, 2005; Molinari et al., 2014). Moreover, the Framework's first 'priority for action' is 'understanding disaster risk', including the development and implementation of methods for risk assessment (UNISDR, 2015).

Dealing with or managing floods has shifted from more of an engineering (design) approach to a risk- (and system-) based approach, recognising that 'flood risk management is about managing human behaviour as much as managing the hydrological cycle' (Hall & Penning-Rowsell, 2011, p. 11). This approach is well reflected by the conceptual risk representation (Figure 1.1).

The process of risk management is based on, or starts with, the risk analysis: the quantitative estimation of risk. When or where there will be a hazardous event, how much, of which type, and whether it will turn into a disaster, are all necessary questions with uncertain outcomes. These and other queries are reflected in the numerical definition of risk (Kron, 2005): the interplay amongst hazard, exposure, and vulnerability (Figure 1.1). Risk analysis is followed by risk evaluation: how much risk is tolerated or accepted by the society (Bell & Glade, 2004). Knowing the consequences is of utmost importance, rather than considering the drivers or the hazard components in isolation.

Each of the three components of risk – hazard, exposure, and vulnerability – has a range of methods of assessment and underlying uncertainties. However, they are frequently studied separately in the attempt to reduce their uncertainties in modelling. With regard to floods, model chains representing meteorology, hydrology, and hydraulics study describe, forecast, and project the hazard. Their boundaries, along with anthropogenic activities, define the directly exposed population and assets, whilst indirect exposure is more complex and dynamic. Characteristics of the exposed assets determine their degree of susceptibility, or damage degree, respective to the hazard at play, representing vulnerability.

Risk analysis methods have been developed from the property to the global scale (Meyer et al., 2013; Ward et al., 2020), but most models still focus on single-hazard events. However, the incidence of multiple hazards consecutively or simultaneously might

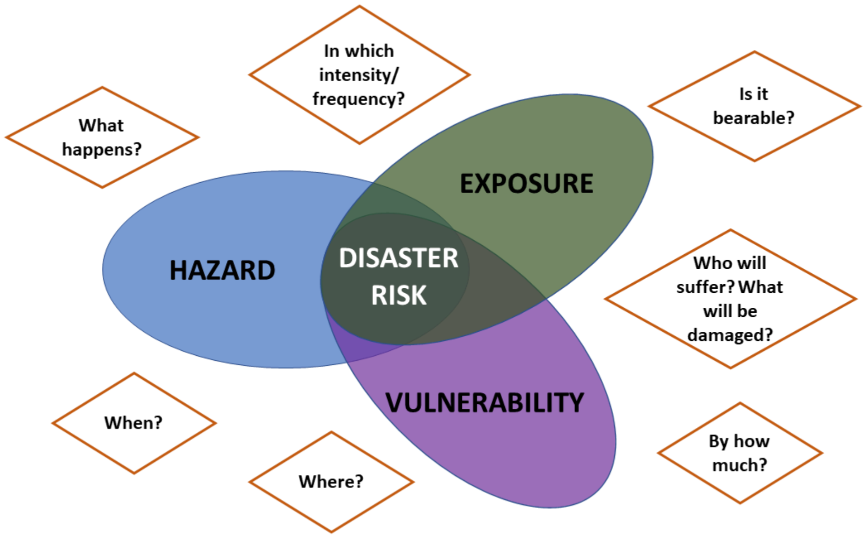

Figure 1.1: Representation of risk (modified from IPCC, 2012)

lead to a higher load than the simple sum of each hazard (Luo et al., 2020). Such events may also result in unexpected or unwanted amplification of the impacts compared to those of each hazard on its own (Kappes et al., 2012; Liu et al., 2015; Luo et al., 2020). However, to what extent the coincidence of hazards exacerbates these impacts is still largely unknown.

The development of multi-risk assessment methods has recently been growing in the scientific community, though focussed on the (multi-) hazard component (Gallina et al., 2016; Kappes et al., 2012). Multi-hazard studies commonly emphasise the interaction of hazards (how the occurrence of one hazard may trigger a consecutive hazard) or the probability of different, though coinciding, hazard types (e.g. earthquakes triggering landslides [Gill and Malamud, 2014; Luo et al., 2020] or riverine floods coinciding with high groundwater floods [Kreibich and Thieken, 2008; Macdonald et al., 2012]). For the case of different hazards, other studies have focussed on the comparability of hazards regarding their intensity, which are presented in different units as one building likely has different vulnerabilities to different physical processes (Kappes et al., 2012; Marzocchi et al., 2012). Nonetheless, methods for assessing (multi-) vulnerability (i.e. the variability of vulnerability amongst different exposed assets or the temporal variability of one asset's vulnerability) remain comparably underdeveloped (Gallina et al., 2016). Multi-vulnerability varies in time and mode (Gallina et al., 2016; Liu et al., 2015; Terzi et al., 2019). Temporal changes in vulnerability may develop in the long-term, which is mostly relevant for projection studies, or in short periods (e.g. in a cascade of events or sequentially occurring hazards) in which the vulnerability of an asset (a building) likely increases after each event as the asset becomes less 'intact' than it was originally (Luo et al., 2020; Marzocchi et al., 2012). Multi-risk studies on multi-vulnerability have addressed its model variability, usually defining and adopting different influencing factors (i.e. predictor variables) to explain the vulnerability of an asset to varying hazards (Gallina et al., 2016; Kappes et al., 2012; Marzocchi et al., 2012; Zuccaro et al., 2018). Such studies, however, have not assessed the different effect of the same influencing factor under various hazards. In plain words, does a one-meter-high riverine flood cause the same damage as a one-meter-high groundwater flood?

Disasters are not (only) natural (Marchezini, 2020) but comprise an interplay between physical forces and anthropogenic activities (see Figure 1.1), sometimes unplanned. Thus, societies can be unaware of potential or even frequent threats or sometimes aware but dismissive of them. Paprotny et al. (2018) have analysed flood events in Europe by normalising population and assets exposure, resulting in a non-significant downward trend in monetary losses and a significant decrease in fatalities over the last decades. This analysis, however, is only of high-impact events, whilst small events could constitute a significant part of losses (Merz et al., 2009) and change the estimation of trends (Paprotny et al., 2018). In addition, the study normalised for exposure only, a common, however, incomplete approach as it dismisses the role of vulnerability change (Mechler & Bouwer, 2015). Numerically representing vulnerability is challenging, but the understanding that human behaviour and risk management can reduce vulnerability or increase coping capacity, resulting in reduced flood losses and fatalities, has been positively identified (Kreibich, Di Baldassarre et al., 2017; Kreibich et al., 2021; Thieken, Kienzler et al., 2016), even though often qualitatively.

This doctoral thesis addresses the vulnerability component by exploring loss models, that is, the degree to which the asset is impacted. The estimation of financial losses is a necessary step for, for instance, risk assessment, risk reduction strategies, design of insurance or relief funds, and policy development (Merz et al., 2010; Meyer et al., 2013; Molinari et al., 2019). However, loss documentation is not yet a standardised procedure, and individual verification is onerous in large events. Therefore, numerical models are an important tool for filling in the gap in loss documentation (*ex post*) and for developing scenarios and projections (*ex ante*) (Gerl et al., 2016; Meyer et al., 2013; Molinari et al., 2020). Nevertheless, loss models have been identified as the most uncertain of the three components of risk (Apel et al., 2009; Jongman et al., 2012; Molinari et al., 2020; Wing et al., 2020) and are thus the subject of this thesis.

1.3 Flood Loss Modelling

Representing a phenomenon with a numerical model is both a tool for prediction and a learning process, through which one can also investigate which information is (more) relevant for simulating or forecasting the studied response and therefore better focus resources (Beven, 2007a, 2007b). Numerical models, such as loss models here addressed, can be based on empirical data (i.e. observed data collected through, e.g., field surveys) or synthetic data (i.e. data sets constructed through a set of "what if" questions and analyses and expert opinions) (Merz et al., 2010; Sairam et al., 2020).

Damage or loss caused by floods may have effects in various forms and at different moments, being commonly classified as tangible or intangible and direct or indirect impacts (Merz et al., 2010; Meyer et al., 2013). This thesis focusses on direct, tangible impacts caused by the direct contact of flood waters with residential buildings (the assets), which can be measured in monetary terms: there are market options for repair or replacement which determine prices and hence values of lost or damaged items (Merz et al., 2010). More specifically, I model the relative financial loss, or loss ratio (i.e. the ratio between the costs of repair and reconstruction of the building and the building's value).

In flood risk assessment, the loss function has been identified as the largest source of uncertainty (Apel et al., 2009; Jongman et al., 2012; Molinari et al., 2020; Wing et al., 2020). The water level is a widespread collected variable and a dominant factor of flood financial loss (Gerl et al., 2016). Thus, many flood loss models have simplified the damage function to a single depth-damage curve, on the general basis that the higher the water level, the higher the loss (e.g. Arrighi et al., 2013; Dutta et al., 2003; Jonkman et al., 2008; and examples in Jongman et al., 2012), but more recent works have shown evidence that the relationship between water level and loss is not always monotonic (Molinari et al., 2020; Wing et al., 2020). Moreover, previous studies have identified numerous factors in loss estimation, from characteristics of the building to the preparedness of the population (Kreibich et al., 2011; Merz et al., 2013; Thieken et al., 2005; Thieken et al., 2008; Vogel et al., 2018). Some flood loss models are based on multiple depth–damage curves, mostly with each curve considering different building characteristics such as building age and type (e.g. Multi-Coloured Manual [MCM], Penning-Rowsell, 2005; HAZUS, Scawthorn et al., 2006). Only a few models consider other explanatory variables addressing alternate aspects of the damaging process, such as preparedness or socioeconomic indicators (Gerl et al., 2016; Gradeci et al., 2019), when, in fact, this has been shown to alter the losses (Hudson et al., 2014).

This thesis uses survey data from affected households undertaken in the aftermath of eight damaging floods in Germany. The surveys aim for the detailed study of the damaging process at the object level and address several aspects of the event, not only the magnitude of the hazard, but characteristics of the affected asset, the socioeconomic condition of the household, aspects of the early warning system, indicators of preparedness, and impacts (Kellermann et al., 2020; Thieken et al., 2017). Surveys were conducted at least seven months after the events, allowing for the households to calculate the actual costs of replacement or repair. Although the surveys were composed of about 180 questions, previous studies (Kreibich et al., 2011; Merz et al., 2013; Thieken et al., 2005; Thieken et al., 2008; Vogel et al., 2018) have filtered potentially important predictor variables, reducing the working dataset to 30 variables on the object level (building), aside from the flood event year and the federal state, as shown in Figure 1.2. Other variables regarding the perception of risk, recovery, psychological burden, and responsibility, were analysed but not included for loss modelling. The surveys total 6000 data points, although not all entries indicated a valid building loss ratio.

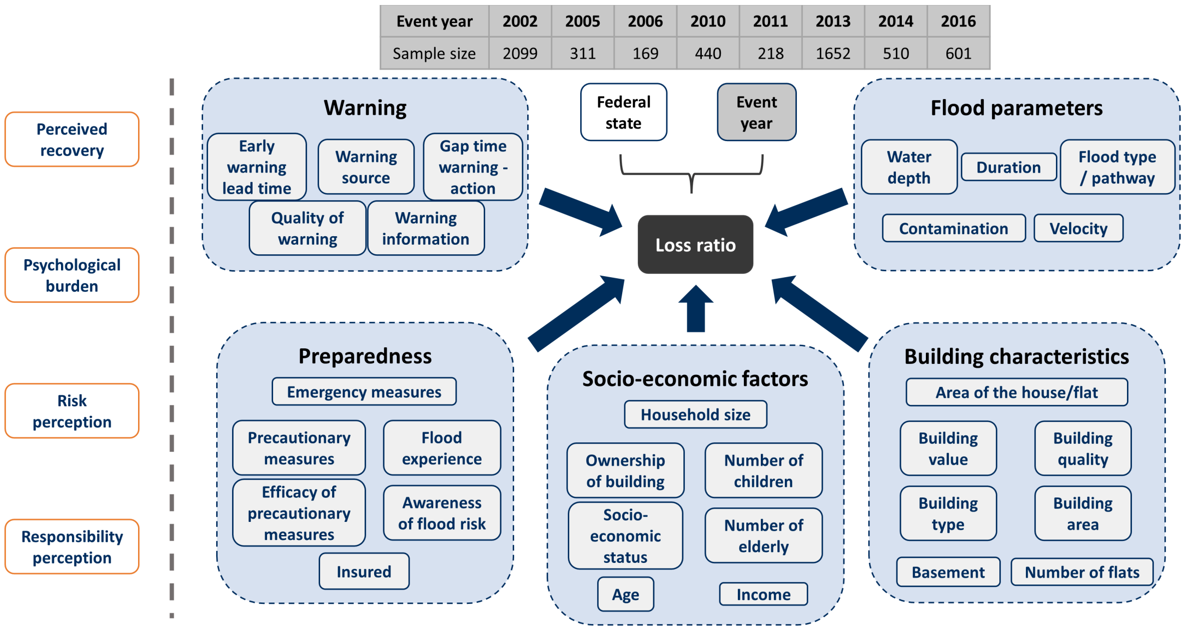

Figure 1.2: Variables from the survey data used in this thesis

Flood loss models are frequently trained using data collected after one specific flood event (empirical data; i.e. real and [potentially] detailed data), which might be validated and can represent a range of conditions. Alternatively, a model can be constructed based on synthetic data. Although synthetic models have the advantage of reducing data variability and obviating the need for intensive data collection, such models rely on assumptions, which may be problematic, especially when regarding behaviour, and are hardly validated as they are frequently constructed when no data are available (Sairam et al., 2020). Numerous model developments based on observed data have been made with relative success in terms of calibration, though they have rarely been validated (Gerl et al., 2016). Applying such models to new events or settings, however, has not been successful, even when models are applied to the same time or space (Cammerer et al., 2013; Figueiredo et al., 2018; Jongman et al., 2012; Schröter et al., 2014). Amongst the reasons for such difficulty is the fact that most models are trained in a singular setting, not able to adapt to or reflect different situations (Wagenaar et al., 2018). One such setting is the flood type.

The transferability of flood loss models (i.e. the application of a model on a setting different than the original setting on which the model was based) is challenging and multi-dimensional (Merz et al., 2010). For example, models may be applied at a different time, space, scale, object, and flood type. Difficulty arises when different elements or features of the modelled system which influence the represented process are unaccounted for or when the available data does not correspond to that used in training the model (Molinari et al., 2020). For instance, across time and space, civil construction can adopt different standards: thus, localities may experience different market pressure and transform, for example, their manufacturing activity into banking activity, which changes the vulnerability, susceptibility, and assets' value (Merz et al., 2010; Penning-Rowsell, 2005). In addition, the awareness and preparedness of the population evolve with time and place, changing their final susceptibility (Kreibich, Di Baldassarre et al., 2017). In regard to scale (micro- to meso- or large-scale applications), the model application may be needed from local to national or even global scales and the level of data aggregation may or not follow the scale of application desired (Molinari & Scorzini, 2017; Sieg et al., 2019). Moreover, within an apparently 'homogeneous' sample of a given location, there is a large variation of susceptibility amongst houses or commercial or industrial sites. Finally, across different flood types (e.g. from riverine to coastal floods), the presence of salt in the water (Penning-Rowsell, 2005), to mention only one factor, can cause losses which are distinct or of different intensity in comparison to losses caused by river floods.

This last dimension evokes the sub-classification of floods and henceforth the coincidence of multiple hazards. Floods are a type of hydro-meteorological hazard, frequently sub-classified but in non-uniform ways. This is discussed in the next section.

1.4 Flood Classifications

Floods have been studied as a reflection of precipitation systems onto the flood's timing and magnitude, but soil condition and land-use properties are also essential for the occurrence of a flood (Teegavarapu, 2012). However, this traditional approach has largely focused on linking precipitation and river streamflow, thus river floods. Floods are not only frequent and damaging but also diverse. Likewise, the classification of floods has been found to be heterogeneous and ambiguous. Table 1.1 compares the terminology used by several large international initiatives (under hydrological, hydrometeorological, or hydroclimatic hazards, i.e., excluding landslides, avalanches, and storms): the IRDR Peril Classification (IRDR, 2014); the initiative led by CRED and Munich RE (Below et al., 2009); the UNISDR Terminology on DRR (UNISDR, 2009); and the types listed in the WMO 'Manual on flood forecasting and warning' (WMO, 2011). Moreover, the recent UNDRR Hazard Definition and Classification Review (UNDRR, 2020) has gathered

Table 1.1: Hydrological hazard or peril classifications

IRDR (2014) (Hydrological)	CRED and Munich RE (2009) (Hydrological)	UNISDR (2009) (Hydrometeorological)	WMO (2011) -Manual on flood forecasting	UNDRR Review (2020) (Meteo- and Hydrological)
Coastal flood	Storm surge/coastal flood	Coastal storm surges	Coastal flood	Coastal flood
			Estuarine flood	Estuarine flood
Riverine flood	General (river) flood	Floods including flash floods	Fluvial (riverine) flood	Fluvial (riverine flood)
Flash flood	Flash flood		Flash flood	Flash flood
			Urban flood	Ponding flood
				Surface water flooding
Ice-jam flood			Ice- and debris-jam floods	Ice-jam flood including debris
			Snowmelt flood	Snowmelt flood
Glacial lake outburst (Climatological)				Glacial lake outburst flood (GLOF)

several sources and presented an 'initial hazard list' compilation, with its definitions published later (Murray et al., 2021).

The sub-classification of flood events has mostly focussed on their triggers or generating conditions, such as the common distinction amongst fluvial, pluvial, and coastal floods, or as suggested in the studies by Hundecha et al. (2020) and Merz and Blöschl (2003), classified as long-rain, short-rain, snowmelt, rain-on-snow, rain-on-dry-soil, or flash floods. Such classification of flood events, however, still overlooks the dynamics or characteristics of flood waters at the immediacy of the affected assets. For example, the hydrostatic and hydrodynamic forces at the building or the presence of debris, oil, or other contaminants which cause chemical processes (Kelman & Spence, 2004; Nadal et al., 2010) are crucial for the understanding of the damaging process and estimation of financial loss.

To account for the specific processes, the term 'flood pathway' has been introduced, following the Source-Pathway-Receptor framework (Hall et al., 2003; Sayers et al., 2002) and reflecting the link between the source (e.g. excessive, prolonged rainfalls) and the receptor (e.g. residential buildings). This terminology has been adopted in this thesis as an intentional distinction to 'flood types' (i.e., fluvial, pluvial, and coastal floods). In other words, this thesis does not strictly follow any specific classification presented in Table 1.1 but further differentiates the classification of flood events as pluvial and fluvial flood 'types' into the following flood 'pathways', reflecting rather the dynamics at the immediacy of individual assets: levee breaches, river floods, surface water floods, and groundwater floods.

In this cumulative thesis, the common term 'flood type' was used in chapters 3 and 4 in reference to 'flood pathway', a clarification/specification which was finally introduced in the development of chapters 2 and 5. As both chapters (3 and 4) have already been published, the term 'flood type' has not been replaced in them.

Despite most studies identifying a flooding event as being of one single flood type or pathway amongst the ones listed above, multiple flood pathways occurring at the same time and space have been reported in Germany and elsewhere (e.g. Chen et al., 2010; Kreibich & Thieken, 2008; Macdonald et al., 2012). Therefore, the question arises regarding how well loss datasets and loss models account for multiple pathways. This thesis addresses multiple flood pathways and their coincidence in loss modelling, focussing on the most frequent pathways observed in Germany: levee breaches, river floods, surface water floods, and groundwater floods. The simultaneous or successive incidence of multiple physical hazards can be referred to as a compound event (IPCC, 2012; Zscheischler et al., 2020). As the coincidence of coastal and fluvial floods is commonly referred to as compound floods, I refer to the coincidence of the four studied pathways as compound inland floods.

Finally, it has been posed that compound events might lead to synergetic effects (i.e. the effect of a compound might be larger than the simple 'sum' of each part). Thus, mostly compound floods – referring to the coincidence of coastal and river floods – have been studied (e.g. Gori et al., 2020; Huang et al., 2021), whilst losses from compound inland floods still, to my knowledge, constitute a gap in the scientific literature, which is addressed by this thesis. This adds another dimension to the loss modelling and the transferability across flood types or pathways since the model must learn or be applied to different settings within the same flood events. For this, Bayesian multilevel models (BMMs) are a particularly useful method capable of simultaneously learning multiple settings, like multiple pathways, within the same dataset and retaining their uncertainty (Gelman et al., 2014; McElreath, 2020). Bayesian models have been previously applied for flood loss estimation (Sairam et al., 2020; Sairam et al., 2019; Schröter et al., 2014; Vogel et al., 2018), although not for the (co)incidence of multiple pathways, which motivates the use of this method in this thesis.

1.5 Purpose and Structure

Despite the importance of floods and the development of various loss models, challenges in the understanding of damage processes, particularly regarding compound processes, and model transferability remain. The knowledge gaps and uncertainties abovementioned lead to the following research questions:

1. In which aspects do flood pathways of the same (compound inland) flood event differ?
2. How much do factors which contribute to the overall flood loss in a building differ in various settings, specifically across different flood pathways?
3. How well can Bayesian loss models learn from different settings?
4. Do compound, that is, coinciding flood pathways result in higher losses than a single pathway, and what does the outcome imply for future loss modelling?

The central part of this thesis is divided into four chapters addressing the respective abovementioned research questions. The chapters are based on a database of surveys on flood-affected households in Germany (Figure 1.2), but each chapter uses a complementary subset, as shown in Table 1.2. The database is suitable for answering the research questions posed, for it includes data at the object level, from multiple flood events, with multiple and coinciding flood pathways, from multiple states of Germany, and addressing multiple aspects of the damaging process.

In chapter 2, survey data from two destructive flood events in Germany are analysed, one mostly of fluvial and the other mostly of pluvial nature. The data from each event is further divided between the most severe flood pathway and all other pathways. Following the cycle of disaster risk management, several aspects of the disaster are compared (e.g. hazard, impacts, warning, preparedness) across events and flood pathways. In chapter 3, survey data from six (mostly fluvial) flood events are divided according to the dominant flood pathway reported amongst the four studied, and factors previously identified as potential loss predictors are statistically compared across pathways. Variable selection processes are implemented for the development of a simple linear regression (ordinary least squares, OLS), showing the general more dominant factors and how they differ under different flood pathways for the estimation of loss ratio. In chapter 4, BMMs are trained for the same dataset. For the different model structure, a new variable selection is performed, this time for three model variants, grouping the dataset across different event years, socioeconomic regions, or flood pathways. Finally, the focus of chapter 5 lies on the multiple and coinciding flood pathways of compound inland floods. Bayesian models are trained with different structures, one to better learn the contribution of each predictor factor for each flood pathway and another to identify potentially added (synergetic) effects of the compound situation. This final study uses the most comprehensive data set.

In this cumulative thesis, I have been the main contributor to the manuscripts presented as chapters 3, 4, and 5, and a contributor to chapter 2.

Table 1.2: Thesis structure

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Research question	1	2	3	4
Flood events	2013 and 2016	2002 - 2013		2002 - 2016
Flood pathway attribution	Interviewee's response and physical processes described in event reports	Interviewee's response		
Flood pathways considered	Levee breaches, flash floods, non-differentiated	Levee breaches, river floods, surface water floods, groundwater floods		
Model approach	Statistical analysis	OLS	BMM	BMM
Grouping variable / Subset	Most intense pathway per event	None OR Flood pathway	Flood pathway OR Region OR Event	Compound flood OR Flood pathway
Model training dataset	—	Complete datapoints (n=1812)	70% of complete datapoints (n=1269)	Complete datapoints from 2010 – 2016 floods (n=1717)
Model test dataset	—	—	30% of complete datapoints (n=543)	Complete datapoints from 2002 - 2006 floods (n=1153)

- Chapter 2: Thieken, A. H., **Mohor, G. S.**, Kreibich, H., & Müller, M. (2021). Compound flood events: different pathways–different impacts–different coping options? Natural Hazards and Earth System Sciences, [accepted]. https://doi.org/10.5194/nhess-2021-27

- Chapter 3: **Mohor, G. S.**, Hudson, P., & Thieken, A. H. (2020). A Comparison of Factors Driving Flood Losses in Households Affected by Different Flood Types. Water Resources Research, 56(4). https://doi.org/10.1029/2019WR025943

- Chapter 4: **Mohor, G. S.**, Thieken, A. H., & Korup, O. (2021). Residential flood loss estimated from Bayesian multilevel models. Natural Hazards and Earth System Sciences, 21(5), 1599–1614. https://doi.org/10.5194/nhess-21-1599-2021

- Chapter 5: **Mohor, G. S.**, Thieken, A. H., & Korup, O. (under review). Estimating the Financial Loss of Residential Buildings under Compound Inland Floods.

Additionally, I have contributed to papers and reports not included in the thesis but closely related to the studied topic.

- Molinari, D., Scorzini, A. R., Arrighi, C., Carisi, F., Castelli, F., Domeneghetti, A., Gallazzi, A., Galliani, M., Grelot, F., Kellermann, P., Kreibich, H., **Mohor, G. S.**, Mosimann, M., Natho, S., Richert, C., Schroeter, K., Thieken, A. H., Zischg, A. P., & Ballio, F. (2020). Are flood damage models converging to "reality"? Lessons learnt from a blind test. Natural Hazards and Earth System Sciences, 20(11), 2997–3017. https://doi.org/10.5194/nhess-20-2997-2020

- Berghäuser, L., Schoppa, L., Ulrich, J., Dillenardt, L., Jurado, O. E., Passow, C., **Mohor, G. S.**, Seleem, O., Petrow, T., & Thieken, A. H. (2021). Starkregen in Berlin: Meteorologische Ereignisrekonstruktion und Betroffenenbefragung. https://doi.org/10.25932/PUBLISHUP-50056

- Thieken, A. H., Kemter, M., Vorogushyn, S., Berghäuser, L., Sieg, T., Natho, S., **Mohor, G. S.**, Petrow, T., Merz, B., & Bronstert, A. (2021). Extreme Hochwasser bleiben trotz integriertem Risikomanagement eine Herausforderung. Potsdam, Germany. https://www.uni-potsdam.de/fileadmin/projects/natriskchange/Taskforces/Flut2021_StatementThiekenEtAl.pdf

- Bubeck, P., Kienzler, S., Dillenardt, L., **Mohor, G. S.**, Thieken, A. H., Sauer, A., Neubert, M., Blazejczak, J., & Edler, D. (2019). Bewertung klimawandelgebundener Risiken: Schadenspotenziale und ökonomische Wirkung von Klimawandel und Anpassungsmaßnahmen: Abschlussbericht zum Vorhaben „Behördenkooperation Klimawandel und -anpassung". Teil 1 (CLIMATE CHANGE 00/2019). Dessau-Roßlau, Germany. https://www.umweltbundesamt.de/publikationen/bewertung--klimawandelgebundener-risiken

Chapter 2

Compound inland flood events: different pathways – different impacts – different coping options? [1]

Abstract Several severe flood events hit Germany in recent years, with events in 2013 and 2016 being the most destructive ones although dynamics and flood processes were very different. While the 2013-event was a slowly rising widespread fluvial flood accompanied by some severe dike breaches, the events in 2016 were fast onset pluvial floods, which resulted in some places in surface water flooding due to limited capacities of the drainage systems and in others, particularly in small steep catchments, in destructive flash floods with high sediment loads and log jams. Hence, different pathways, i.e. different routes that the water takes to reach (and potentially damage) receptors, in our case private households, can be identified in both events. They can thus be regarded as spatially compound flood events or compound inland floods. This paper analyses how differently affected residents coped with these different flood types (fluvial and pluvial) and their impacts while accounting for the different pathways (river flood, dike breach, surface water flooding and flash flood) within the compound events. The analyses are based on two data sets with 1652 (for the 2013-flood) and 601 (for the 2016-flood) affected residents who were surveyed around nine months after each flood, revealing little socio-economic differences–except for income–between the two samples. The four pathways showed significant differences with regard to their hydraulic and financial impacts, recovery, warning processes as well as coping and adaptive behaviour. There are just small dif-

[1] This chapter has been accepted for publication as Thieken, A. H., Mohor, G. S., Kreibich, H., & Müller, M. (2021). Compound inland flood events: different pathways–different impacts–different coping options? Nat. Hazards Earth Syst. Sci., https://nhess.copernicus.org/preprints/nhess-2021-27/

ferences with regard to perceived self-efficacy and responsibility offering entry points for tailored risk communication and support to improve property-level adaptation.

2.1 Introduction

Floods are the most frequent natural hazard worldwide affecting the most people (CRED and UNDRR, 2020), with Europe being no exception (European Environment Agency, 2019). Among these, different flood types can be distinguished (de Bruijn et al., 2009):

- coastal flooding, i.e. when sea water inundates land; - fluvial flooding, i.e. when rivers overtop their banks or embankments fail; - pluvial flooding with areal inundations after heavy rainfall, e.g., due to limited drainage capacities.

These flood types can occur separately or simultaneously, e.g., the coincidence of coastal and fluvial flooding is commonly referred to as compound event. Originating from research on climate change, compound events are described as (1) simultaneous or successively occurring (climate-related) events such as simultaneous coastal and fluvial floods; 2) events combined with background conditions that augment their impacts such as rainfall on already saturated soils; or (3) a combination of (several) average values of climatic variables that result in an extreme event (IPCC, 2012; Pescaroli & Alexander, 2018). However, recent inland floods revealed features of compound events. For example, severe flooding in 2002 caused losses of over EUR 21 billion in Central Europe (European Environment Agency, 2019). During this flood event, the city of Dresden in Saxony, Germany, was hit by four consecutive flood waves, which were all triggered by the same rainfall event: first, surface water flooding occurred in the city as an immediate response to the heavy precipitation on 12 August 2002 and the limited capacity of the sewer system, which was shortly, i.e. on the next day, followed by a flash flood from the local and mid-sized rivers Weißeritz and Lockwitzbach that drain into the bigger river Elbe within the city area of Dresden. A few days later, i.e. on 17 August 2002, this flooding was followed by inundations from the flood wave of the river Elbe, which was later followed by high groundwater levels lasting for several months (Kreibich, Petrow et al., 2005). Further downstream of the river Elbe, dike breaches caused huge inundations of the hinterland (DKKV, 2003). Zscheischler et al. (2020), however, termed a situation in which multiple locations are impacted within a limited time window and are connected via a physical modulator, i.e. the atmospheric circulation, spatially compound events. To avoid confusion with the coincidence of river and coastal flooding, we use the term compound inland flood in this paper.

Following the source-pathway-receptor-consequences model (SPRC-model; e.g. Sayers et al., 2002), the different processes observed in Dresden and downstream in 2002 can also be regarded as specific pathways within a regional flood event, since the floodwater takes a different route to reach (and potentially damage) receptors such as buildings or residents. In flood impact analyses or loss modelling, compound inland floods with different pathways have rarely been studied although there are indications that the resulting consequences differ. For example, buildings affected by dike breaches tend to experience higher losses than buildings affected by a usual river flood (Cammerer & Thieken, 2011; Mohor et al., 2020). Overall analyses of data from fluvial floods between 2002 and 2013 suggest that different flood pathways, i.e. river floods, dike breaches, surface water flooding and groundwater floods, play an important role when it comes to the assessment of (financial) flood impacts (Mohor et al., 2020; Mohor et al., 2021; Vogel et al., 2018). Differences in coping options during the event as well as in recovery in its aftermath are less clear. For example, the widespread flood of June 2013 demonstrated improved flood risk management all over Germany (Thieken, Bessel et al., 2016; Thieken, Kienzler et al., 2016). This most severe flood event in hydrological terms (Merz et al., 2014; Schröter et al., 2015) caused lower losses, i.e. EUR 6 to 8 billion, than the 2002-flood with EUR 11.6 billion (Thieken, Bessel et al., 2016; Thieken, Kienzler et al., 2016). Still, some areas, particularly those affected by dike breaches, suffered from severe losses. To mitigate future damage, this pathway needs further attention.

Next to fluvial floods, pluvial flooding has occurred in several places in Germany in recent years, e.g., in the city of Münster in 2014 (Spekkers et al., 2017) or in the village of Braunsbach in 2016 (Bronstert et al., 2018), causing damage that was unprecedented for this type of flooding. Particularly the event of May/June 2016 challenged (local) water authorities, emergency responders and residents: several places in Germany were affected by heavy rainfall and hail leading to surface water flooding due to limited capacities of urban drainage systems (Gesamtverband der Deutschen Versicherungswirtschaft, 2016; Piper et al., 2016). Moreover, in some places, particularly in the small towns of Braunsbach (located in the federal state of Baden-Wurttemberg) and Simbach (located in the Freestate of Bavaria), flooding was accompanied by quick concentrated surface runoff activating huge amounts of mud, debris and further material that was carried downstream, blocked culverts and threatened people and assets (Bayerisches Landesamt für Umwelt, 2017; Hübl et al., 2017; Laudan et al., 2017; Piper et al., 2016; Vogel et al., 2017). Overall losses amounted to EUR 2.6 billion (Munich RE, 2017), eleven people lost their lives and more than 80 people were injured, mostly by lightning strokes.

Analyses of pluvial floods illustrate that warning is more difficult and residents tend to be less experienced with this flood type and are hence less prepared for it, but average property losses are commonly lower in comparison to fluvial floods (compare Kienzler et al. 2015 with Gesamtverband der Deutschen Versicherungswirtschaft 2020; Kind et al. 2019; Rözer et al. 2016; Spekkers et al. 2017). These analyses, however, mainly focussed on surface water flooding in urban areas, ignoring that impacts caused by flash floods with sediment loads can be exceptionally high (Gesamtverband der Deutschen Versicherungswirtschaft, 2016; Laudan et al., 2017), which was emphasized by flooding in July 2021 in Western Germany that caused more than 180 fatalities and losses of around 30 billion EUR in Germany. The severity of flash flood processes also affected mental health as well as precautionary behaviour (Laudan et al., 2020) and even led to relocations of some buildings at risk, a risk management strategy that has been rarely implemented in Germany (Mayr et al., 2020). Hence, to better understand flood impacts and coping options, it seems necessary to not only distinguish different flood types (fluvial and pluvial flood), but also different pathways within one flood event, like dike breaches during fluvial floods and flash floods with sediment loads during pluvial floods.

Accounting for interactions between hazard processes helps to better understand and prepare for complex events. In this context, compound, interacting and cascading events are distinguished (e.g. Pescaroli & Alexander, 2018). We argue that the flood events of 2002, 2013 and 2016 in Germany that were described above can be understood as compound flood events since rainfall from a common atmospheric circulation led to different flood situations depending on the antecedent soil moisture, the characteristics of the catchment (e.g., topography, size, land use, drainage network) and/or the failure of flood protection. Zscheischler et al. (2020) further recommend separating and analysing different elements, i.e. pathways in our view, to better understand the event as a whole. Hence, the term compound inland flood is used for floods that unfold different damaging pathways while being connected through the same triggering event.

Furthermore, event-oriented storyline approaches were proposed to link climate change to societal impacts in order to improve disaster risk management (Shepherd et al., 2018; Sillmann et al., 2021). Therefore, we created subsamples that capture different flood pathways, i.e. dike breaches, river floods, flash floods (with sediment loads) and surface water flooding, to study their characteristics within and between the two flood events of 2013 and 2016 (see section 2.2 and 2.3.3). We hypothesize that such in-depth analyses of impact and coping patterns of different flood types and pathways provide entry points to derive storylines and to better tailor flood risk management to local circumstances. In particular, this paper aims to reveal whether and how differently people were affected by different flood types and pathways, how much they were impacted in hydraulic, financial and psychological terms, and how differently they were prepared before the damaging event, coped with it and recovered from the impacts. The intention is to provide empirically-based, quantitative insights that help establish risk management strategies tailored to different flood types and pathways.

Like in previous studies (Kienzler et al., 2015; Thieken et al., 2007, for fluvial floods and Rözer et al., 2016; Spekkers et al., 2017, for pluvial floods) the risk management cycle is used as guiding framework. However, in contrast to the previous studies this paper also looks at patterns within the compound inland flood events separating cases affected by dike breaches in 2013 and flash floods with heavy sediment loads in 2016 from the overall samples to better understand the impacts of and coping options towards specifically challenging pathways. For clarity, general flood types are termed fluvial and pluvial floods in this paper, while pathways within the events are named dike breach, river flood, surface water flood and flash flood.

2.2 The compound inland floods of 2013 and 2016

2.2.1 The flood of June 2013

In June 2013, widespread fluvial flooding occurred in Central Europe, particularly in Germany: twelve out of 16 German federal states were affected; eight of them declared a state of emergency (BMI, 2013 as cited in Thieken, Bessel et al., 2016; Thieken, Kienzler et al., 2016). Flooding was triggered by a combination of wet antecedent conditions and high precipitation amounts between 31 May and 2 June 2013 (Merz et al., 2014; Schröter et al., 2015). By the end of May 2013, record-breaking antecedent soil moisture was recorded in 40% of the German territory (DWD, 2013) and above-average initial streamflows were observed in many rivers (Thieken, Kienzler et al., 2016). Hotspots of precipitation between 31 May and 3 June 2013 totalled up to 346 mm within 72 hours at the official DWD weather station of Aschau-Stein (Schröter et al., 2015). This combination resulted in high flood peaks in the upper catchments of the rivers Rhine and Weser and particularly in many parts of the catchments of the rivers Danube and Elbe (Thieken, Kienzler et al., 2016). Altogether, peak flows exceeded the five-year flood discharge in 45% of the German river network (Schröter et al., 2015). Around 1,400 km of the river network saw 100-year flood discharges. Hydrological and statistical analyses indicated that this event was Germany's most severe fluvial flood over the past 60 years (Merz et al., 2014) leading to widespread inundations, particularly along the rivers Danube and Elbe. Although huge investments had been made in upgrading embankments after the 2002-flood, some dike breaches and consequent inundations of their hinterland occurred. Three breaches were particularly severe (Merz et al., 2014): (1) a breach at Deggendorf-Fischerdorf at the confluence of the rivers Isar and Danube flooded several properties in Bavaria; due to floating and bursting oil tanks and consequently highly contaminated flood water, 150 homes had to be completely rebuilt (Bavarian Parliament, 2014); (2) a breach in Klein Rosenburg-Breitenhagen at the confluence of the rivers Saale and Elbe in Saxony-Anhalt and (3) a breach near Fischbeck at the middle reach of the Elbe River in Saxony-Anhalt that also affected the high-speed train connection between Berlin and Hanover which was disrupted for several months (Thieken, Bessel et al., 2016). In all of Germany, 14 people died and direct losses summed up to EUR 8 billion (Thieken, Bessel et al., 2016).

In comparison to regions flooded by a river, areas affected by dike breaches tend to suffer from extended inundation durations (Vogel et al., 2018) and – where oil heating is common – floating and leaking oil tanks that cause considerable material and environmental damage (DKKV, 2015; Thieken, Bessel et al., 2016). Considering the triggering mechanism of this flood, as well as the dike breaches mentioned above, this event can be understood as a spatially compound event. To account for different flood pathways, residents affected by "normal" river floods and residents affected by dike breaches are analysed separately in this paper.

2.2.2 Flooding in May and June 2016

From May 26 to June 9, 2016, Germany and parts of central and southern Europe were hit by an extraordinarily high number of severe convective storms with intense rainfall and hail. This thunderstorm episode was caused by the interaction of high atmospheric moisture content, low thermal stability, weak wind speed and large-scale lifting by surface lows (Piper et al., 2016). Low wind speed at mid-tropospheric levels led to nearly stationary or slow-moving convective cells and hence to locally extreme rain accumulations exceeding 100 mm within 24 hours. Due to atmospheric blocking these boundary conditions persisted for almost two weeks (Piper et al., 2016). Depending on the characteristics of the affected catchments and areas the heavy precipitation triggered surface water flooding (due to limited sewer capacity, e.g. in the city of Hanover in Lower Saxony), inundations along (small) rivers and creeks and flash floods, partly carrying huge amounts of mud and debris. The main hotspots occurred in South Germany. In Braunsbach, a small village in Baden-Wuerttemberg, the extreme precipitation of more than 100 mm within 2 hours on May 29 caused a devastating flash flood (Bronstert et al., 2017). The Orlacher Bach, a creek that runs through the village with just 6 km^2 catchment size and very steep slopes, showed extreme runoff with massive debris transport of 42,000 m^3 (Vogel et al., 2017). Streets were blocked with gravel and stones up to a thickness of 2 to 3 m producing immense damage to buildings and infrastructure (Laudan et al., 2017). In Simbach, a village in south Bavaria, situated on the river Inn, the rainfall amounted to 120 mm in 24 hours on June 1 (Piper et al., 2016). Subsequently the small river Simbach (33 km^2 catchment size) and its tributaries showed extreme runoff. At the gauging station Simbach the water level rose from 50 cm to 506 cm within 14 hours. Several culverts were blocked with debris and driftwood, dams broke and parts of the village were flooded (Bayerisches Landesamt für Umwelt, 2017).

In all of Germany eleven people died and the economic loss amounted to EUR 2.6 billion which is extraordinary high with regard to heavy rainfall and thunderstorms in Germany (Gesamtverband der Deutschen Versicherungswirtschaft, 2016; Laudan et al., 2017; Munich RE, 2017; Vogel et al., 2017). Because of the huge losses in Simbach and other villages in Bavaria a grant and loan programme for compensating flood damage to residential buildings and household contents was implemented (Bavarian State Government, 2016). In Baden-Wurttemberg, the market penetration of insurance against natural hazards is still high, i.e. around 94%, due to the fact that it was mandatory until 1994 (Gesamtverband der Deutschen Versicherungswirtschaft, 2020; Surminski & Thieken, 2017).

Since different types of flooding and various runoff dynamics could be observed from May 26 to June 9, this event is also treated as a spatially compound inland flood in this paper. The dynamics comprise different pathways, flow velocities, water depths as well as different impacts that are difficult to categorise distinctly. Yet, households have been mainly affected by shallow surface water flooding, but, in fewer cases, also by the forceful overflowing of water bodies and partly log jams and subsequent dam breaches which led to strong flash floods with a heavy sediment load (e.g. in Braunsbach and Simbach). Thus, the data set from this pluvial flood was separated into cases affected by low/medium surface water flooding on the one hand and cases that suffered from flash floods with debris flows on the other hand (Figure 2.1; see section 2.3.3 for details).

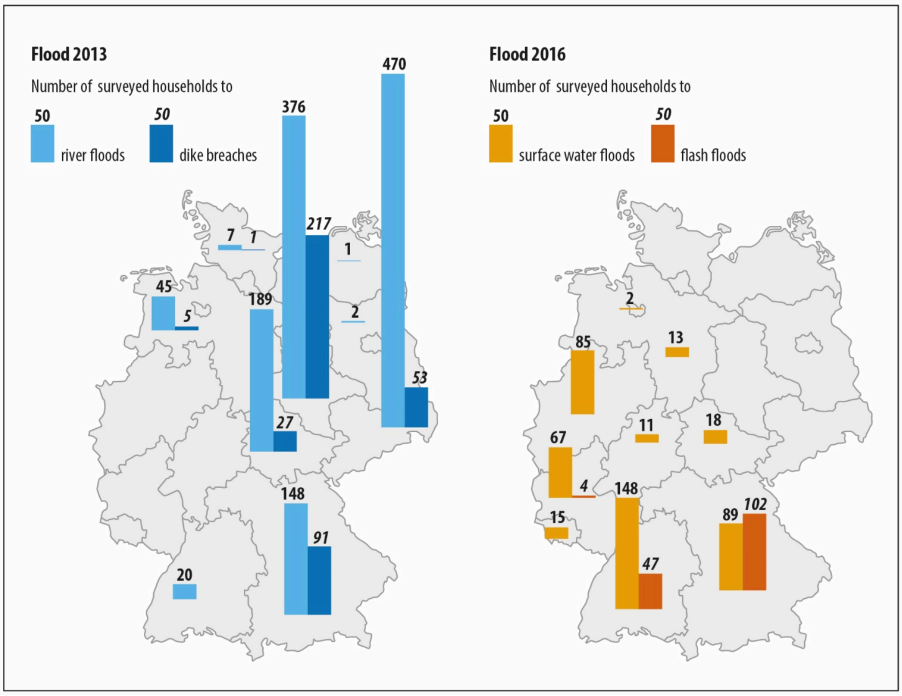

Figure 2.1: Geographic overview of the number of households surveyed about the flood of 2013 (left) and 2016 (right)

2.3 Data and Methods

The analyses are based on survey data that were gathered among private households that suffered from property damage caused by flooding in 2013 or 2016. Both surveys were conducted around nine months after the respective damaging event using computer-aided telephone interviews (CATI), during which residents were guided through a standardized questionnaire (see Thieken et al., 2017). On average, an interview lasted around 30 minutes.

2.3.1 Sampling flood-affected households

To identify affected households, media reports and satellite images were used to compile a list of inundated streets and zip codes. In some cases, this information was provided by affected communities and districts or fire brigades. The lists served as a basis for retrieving telephone numbers (landlines) from public telephone directories. Due to a high number of non-affected residents within the areas identified, all retrieved telephone numbers were finally called. Always the person in the household who had the best knowledge about the flood event was questioned. The surveys were conducted by a subcontracted pollster from 18 February to 24 March 2014 for the 2013-flood and from 28 March to 28 April 2017 for the 2016-event. In total, 1652 interviews from 173 different municipalities across nine federal states were completed for the 2013-flood (out of a total of 43,281 numbers, from which 16,554 could not be reached during the field time; another 16,721 residents did not suffer from financial damage and 8144 refused to participate). For the 2016-event, it was possible to complete 601 interviews in 76 different municipalities spread across nine federal states of Germany (out of 42,487 retrieved numbers, from which 24,486 could not be reached during the field time; 12,010 residents did not suffer from financial damage and 4254 refused to participate).

2.3.2 Contents of the questionnaire and data processing

The questionnaires already presented by Rözer et al. (2016) and Thieken et al. (2007), Thieken et al. (2005) were slightly adapted for the two surveys and contained about 160 questions addressing a range of topics: source of flooding (pathway), depth, velocity and duration of the inundation at the affected property, contamination of the flood water, flood warnings, emergency measures, characteristics of and amount of damage to household contents and buildings, recovery and psychological burden of the interviewed person, precautionary measures, previously experienced flood events, perceived threat and coping appraisal, as well as socio-demographic information. In both surveys, tenants were only asked about their household, the damage to contents and some core characteristics of the building. Several questions used an ordinal Likert-type scale from 1 to 6, where just the meanings of the end points were explicitly verbalized to enable quantitative analyses.

After the collection, data was post-processed through comparisons and consistency checks. While questions about characteristics of the building, e.g., the existence of a cellar, and the type of the losses were cross-checked during the survey, additional checks were performed in the aftermath, e.g., the size of the household was compared to the reported numbers of children and elderly in that household. In addition, some items were aggregated to indicators as described by Laudan et al. (2020) and Thieken et al. (2005): contamination, source of the flood warning, emergency measures (short-term; performed during the event), precautionary measures (long-term measures, implemented before or after the flood) and previously experienced flooding.

Further, the total asset values of contents and buildings were estimated based on the floor space (of the flat or the building) and standardized values. For contents, a unit value of 650 EUR/m^2 as of 2005 was scaled to the year of the event by a consumer price index excluding food, resulting in 695.90 EUR/m^2 (as of 2013) and 719.52 EUR/m^2 (as of 2016). The total value of a building was estimated by the "Mark1914"-insurance value per m^2 per building type multiplied by the "Gleitender Neuwertfaktor" (16.2 for 2013 and 17.2 for 2016), a specific building price index used by the German insurance industry. If the reported damage exceeded the so-estimated asset value, a loss ratio of 1 was assumed. For the comparisons in this study, all monetary values of 2013 were scaled to 2016 based on price indices.

2.3.3 Subsamples

To study differences in flood pathways the following subsamples were distinguished (compare Figure 2.1):

- 2013-dike breaches: all households that reported that they had been affected by a dike breach were included in this subsample; this applied to 394 cases from more than 60 different places across six federal states, i.e. to around 24% of all surveyed cases affected by flooding in 2013;

- 2013-river flooding: all other households from the 2013-data set, i.e. 1258 cases (76%) located in more than 160 municipalities across nine federal states;

- 2016-flash floods: all surveyed households from areas that had been affected by severe flash floods accompanied by sediment loads, log jams or failure of flood protection (see below); this applied to 153 cases from ten different municipalities located in three different federal states, i.e. to around 25% of all surveyed cases affected by flooding in 2016;

- 2016-surface water flooding: all other households from the 2016-data set, i.e. 448 cases (75%) from 66 different municipalities across nine federal states.

The places of cases that reported dike breaches in the 2013-survey were cross-checked with the three locations of severe levee breaches (see section 2.1), revealing that at least 74 cases can be linked to the breach at Deggendorf-Fischerdorf, 129 to the breach in Klein Rosenburg-Breitenhagen and 62 to the breach near Fischbeck (Elbe) illustrating that the answers of the respondents are credible.

Since different pathways of the pluvial flooding in 2016 were more difficult to be distinguished by lay people and were not well captured by the survey questions on the damaging flood pathways, event analyses and reports were used to identify places that were hit by rapid onset floods that were accompanied by huge sediments loads, debris flow, log jams and/or failure of flood protection. Such event characteristics were described for the municipality of Braunsbach in Baden-Wurttemberg (e.g. Bronstert et al., 2018; Laudan et al., 2017) as well as for Künzelsau und Forchtenberg based on field inspections (Mühr et al., 2016). In Bavaria, similar damaging processes were described for the municipalities of Ansbach, Flachslanden, Julbach, Obernzenn, Simbach, and Triftern (Bayerisches Landesamt für Umwelt, 2017; Hübl et al., 2017). An overtopped flood retention basin was reported for the municipality Grafschaft in Rhineland-Palatinate (Demuth et al., 2016). All cases from these municipalities were included in the flash flood sample.

2.3.4 Data Analysis

Data subsets were compared either through the nonparametric Mann-Whitney--Wilcoxon two-sample test or Chi-Squared contingency table test, depending on whether a variable was metric or categorical (Noether, 1991), comparing the median of differences or the closeness of expected frequencies, respectively.

A p-value threshold was set to 0.05 for statistical significance, regardless of the absolute difference or effect size. These procedures were run with R language (R Core Team, 2017) – with the assistance of the packages "stats", "rcompanion", and "PMCMR". For variables with significant differences further statistics were calculated in SPSS. Means and frequencies are presented in relation to the valid answers, i.e. ignoring no answers or "I don't know" entries.

2.4 Results and Discussion

In this section we present the main differences and commonalities between and within the two compound inland flood events. Per topic we will first compare the fluvial 2013-flood to the pluvial 2016-flood, which is then followed by a comparison of the flood pathways within each compound event, i.e. river floods versus dike breaches for the 2013-event as well as surface water floods versus flash floods in 2016.

2.4.1 Socio-demographic characteristics of the subsamples

This section presents the characteristics of the surveyed residents in the four subsamples. Besides the mean values for each item and each subsample as well as for the whole data set, Table 1 provides the test statistics of the Mann-Whitney-Wilcox or Chi-Square tests when comparing all data from the 2013-flood with the 2016-flood as well as when comparing the two subsamples (pathways) within each event.

On a 5%-significance level, Table 1 reveals that socio-demographic characteristics do not differ between the two events, except for the share of households with a monthly net income below EUR 1500 and the share of one-family homes. Both values are higher for the 2013-flood, reflecting that more rural areas were affected by this widespread fluvial flood. Those affected by surface water flooding in 2016 had the smallest percentage of households with income below EUR 1500 or, in other words, a higher share of higher-income households than the other subsamples, as well as the smallest percentage of households living in one-family homes reflecting that mainly urban areas were affected by this flood pathway. In contrast, the flood of 2013 widely affected rural areas in the Eastern parts of the country. The 2013-sample contains many cases from Saxony and Saxony-Anhalt (see Fig. 2.1); in East Germany the mean monthly net income per household amounted to EUR 2521 in 2013, while it was EUR 3297 in West Germany that was hit by the 2016-floodings (Destatis, 2018, see Fig. 2.1). So, the differences in income in our data reflect the regional income pattern in Germany.

In addition, there are slight (i.e. low-significant) differences between the two events with respect to the mean household size and homeownership (Table 2.1). However, these variables differ more pronounced between the two subsamples of the 2013-flood: surveyed households affected by river flooding had the smallest household size and the lowest percentage of home/apartment ownership (80%), whilst those affected by dike breaches showed the highest percentage of homeowners (92%). Similarly, the 2013-river subsample shows a lower share of one-family homes (51%) than the 2013-dike subsample (71%). This suggests that areas affected by dike breaches were mostly rural areas with owner-occupied dwellings and larger families, while other areas affected in 2013 are probably located in more urban settings, also showing a better education and a higher mean age. Similar, but statistically weaker differences were found for the 2016-event. Here the regions affected by flash floods slightly tend to contain more one-family homes, a lower age and less people with a high-school graduation than areas affected by surface water flooding. Still, there are no significant differences in the living area per person among the subsamples, despite a range between 55 m² (river floods) and 64 m² (flash floods). Often, the flash flood subsample did not show high statistical differences to other subsamples, even when presenting the highest or smallest means due to its smaller number of cases (Table 2.1).

Altogether, the characteristics of the four subsamples lie within previous studies' averages, though with varied sample sizes and from different regions in Germany, which should be taken into account when interpreting further results. Previous works compared the socio-economic characteristics of survey respondents to a city or a national census. Some differences are noticeable such as a higher age and a greater share of ownership among respondents, probably because only fixed landlines were consulted. Given the similarity of sampling methods, we expect similar biases in all sub-samples. For a more detailed discussion of potential biases, see the works of Kienzler et al. (2015), Rözer et al. (2016) and Spekkers et al. (2017). Nevertheless, all sub-samples contain data from several municipalities and federal states reflecting different geographic, social and governance contexts across Germany. Even the smallest sub-sample of the flash floods contains 153 cases from ten municipalities located in three different federal states (Figure 2.1) allowing us to draw conclusions beyond the studied events in Germany.

2.4.2 Flood characteristics

The hydraulic impacts of the flood events on the affected buildings are presented in Table 2.2 in terms of water level, flood duration, flow velocity, and the presence of contamination by oil, which all differ significantly between the events of 2013 and 2016 as well as within the two events (except for flow velocity in the case of the 2013-flood). There is a clear difference in water level from surface water floods, which mostly affected only the cellar of houses (indicated by negative values in Table 2.2), followed by river floods to cases of dike breaches and flash floods, which showed the highest mean water level. Negative average water levels, i.e. a water level below the ground surface, were also reported for pluvial and fluvial floods in 2005 (Kienzler et al., 2015; Rözer et al., 2016), a frequent river flood in 2011 (Kienzler et al., 2015) and the Danube area affected in 2002 (Thieken et al., 2007). Hence, the mean water level roughly reflects the intensity of the event.

Surface water and flash floods have considerably shorter durations than river floods and dike breaches (Table 2.2). This pattern is also noticed by Kienzler et al. (2015), given that floods in 2002, 2006 and 2011 with an average duration of more than four days had a predominance of riverine flood dynamics, whilst Rözer et al. (2016) found shorter durations, less than one day in average, for pluvial floods. This pattern of the pathways is reflected in our samples roughly confirming the approaches how the subsamples of the pathways were created.

Of those who were affected by river floods or dike breaches only around 15% reported a very high water velocity, i.e. a value of 5 or 6 on a scale from 1 to 6, in contrast to 65% in

Table 2.1: Socio-demographic characteristics of households affected by different flood pathways in 2013 and 2016

Subsample (Pathway)	River2013	↔	Dike2013	2013 ↔ 2016	Surface2016	↔	Flash2016	Overall
Sample size	1258	—	394	—	448	—	153	2253
Socio-economic and demographic variables								
Female interviewee [%]	59.1		55.3		58.0		53.6	57.8
Mean age of the interviewees [years]	60.4	****	57.1		59.2	.	57.1	59.3
People with high school graduation (Abitur) [%]	34.9	**	27.4		36.1	*	24.1	33.1
Mean household size [number of people]	2.4	****	2.7	.	2.6		2.7	2.5
Households with a monthly net income <1500EUR [%]	35.6		35.4	****	15.9		20.6	30.3
Mean living area per person [m^2]	55.1		58.0		60.4		64.4	57.5
Homeowners (house or apartments) [%]	79.7	****	92.1	.	85.9		86.3	83.6
One-family homes [%]	50.9	****	71.0	****	39.5	.	49.0	52.1

Percentage or means only regarding valid values, i.e. answered entries.
Comparison of subsets or 2013 to 2016 in the middle columns, with P-value ranges from Mann-Whitney-Wilcox or Chi-Square tests represented as: Legend: '****' $\leq$ 0.001 '***' $\leq$ 0.005 '**' $\leq$ 0.01 '*' $\leq$ 0.05 '.' $\leq$ 0.1 ' ' $\leq$ 1

case of flash floods and 28% in case of surface water floods. The percentage of cases that reported oil contamination was the lowest in surface water floods (3%), followed by river floods (12%) and the flash flood subsample (24%). The highest value (34%) was reported by residents who were affected by dike breaches (see Table 2.2). A similar pattern is revealed for other contaminants like sewage, chemicals or petrol (Figure 2.2).

Altogether Table 2.2 illustrates that the people affected by different flood pathways had to cope with significantly different hazard situations, particularly in terms of water levels, flood duration and oil contamination. In addition, residents affected in 2016 by flash floods had to cope with high flow velocities. These findings confirm that our subsamples represent significantly differing flood pathways, while their socio-demographic characteristics differ comparatively little (see section 2.4.1). The next section looks into the financial flood impacts and recovery before we address coping options and strategies.

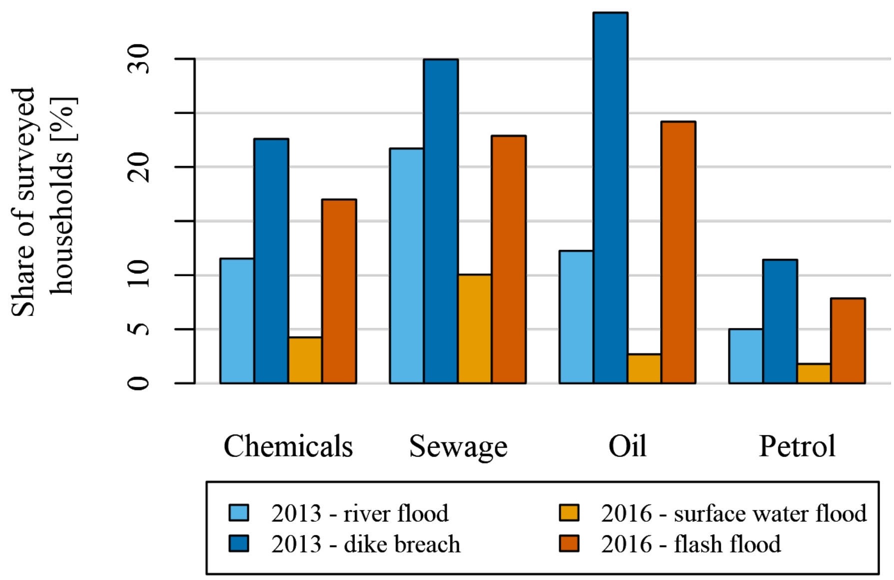

Figure 2.2: Contaminants in the flood water as reported by households affected by different flood pathways in 2013 and 2016 (multiple answers possible)

2.4.3 Financial flood impacts and perceived recovery

The average financial losses of buildings and household contents differ significantly between and within the flood events (Table 2.3). Here, the financial loss refers to the repair and replacement costs (in prices of 2016). Residents affected by flash floods suffered from the highest financial losses – in absolute numbers as well as in terms of loss ratios, followed by those affected by dike breaches and river floods. Losses caused by surface water flooding resulted in the lowest amounts (in absolute numbers as well as with regard to loss ratios; see Table 2.3). Overall, the significant differences in the flood processes and

Table 2.2: Hydraulic flood characteristics and impacts reported by households affected by different flood pathways in 2013 and 2016

Subsample (Pathway)	River2013	↔	Dike2013	2013 ↔ 2016	Surface2016	↔	Flash2016	Overall
Sample size	1258	—	394	—	448	—	153	2253
Mean water level above top ground surface [cm]	46.4	***	76.3	****	-112.8	****	82.8	23.7
Mean flood duration [hours]	173	****	312	****	41	****	36	164
Cases [%] that reported very high flow velocity, i.e. 5 or 6 on a scale from 1= no flow to 6 = very high velocity/ turbulent flow	15.2		15.5	****	28.5	****	65.5	21.1
Cases that reported oil contamination [%]	12.2	****	34.3	****	2.7	****	24.2	15.0

Percentage or means only regarding valid values, i.e. answered entries.
Comparison of subsets or 2013 to 2016 in the middle columns, with P-value ranges from Mann-Whitney-Wilcox or Chi-Square tests represented as: Legend: '****' $\leq$ 0.001 '***' $\leq$ 0.005 '**' $\leq$ 0.01 '*' $\leq$ 0.05 '.' $\leq$ 0.1 ' ' $\leq$ 1

the resulting hydraulic loads presented in Table 2.2 are reflected in the adverse effects of the floods.

To capture the status of recovery at the time of the survey, i.e., 8 to 10 months after the damage occurred, payments received to compensate losses were recorded. Further, respondents were asked to assess the accomplishment of the replacement of damaged household items or of the repair works at the damaged building on a Likert-scale. On a similar scale, they were asked to assess the psychological burden the flood still had at the time of the survey. Table 2.3 reveals that all variables except for the perceived status of the replacement of damaged household items significantly differ between 2013 and 2016. In addition, there are highly significant differences between the pathways within the two events. In general, respondents affected in 2016 received higher pay-outs, assessed their recovery a bit better and felt less burdened than those affected in 2013. However, those who experienced a flash flood in 2016 recovered less and felt more burdened than those affected by surface water flooding. Similarly, residents affected by dike breaches in 2013 are worse off than those affected by river flood.

Altogether, the recovery status around nine months after the damaging event is worse for households affected by the stronger pathways, i.e. dike breaches in 2013 or flash floods in 2016, compared to the low/medium pathways, i.e. river floods in 2013 or surface water floods in 2016. It should be noted that the financial damage was the most severe for flash floods, while the psychological burden and the perceived recovery were the worst for residents who experienced dike breaches in 2013, who are then followed by the flash flood cases (Table 2.3). Maybe the better recovery among severe cases in 2016 is owing to the stronger community resilience that was found to buffer psychological burden in Simbach and surroundings (Masson et al., 2019) as cases from Simbach constitute almost 37% of this subsample (57 of 153 cases). Therefore, this finding needs more cases studies for a confirmation. Furthermore, it is striking that the average pay-outs for loss compensation are – in relation to the mean financial losses – considerable higher for the cases affected by the 2016-floods in comparison to the 2013-flood. Again, this could be due to the local specifics, e.g. the high insurance penetration in Baden-Wurttemberg (Gesamtverband der Deutschen Versicherungswirtschaft, 2020) and the compensation programme in Bavaria (Bavarian State Government, 2016).

In general, financial losses, recovery and psychological burden show highly significant differences between the two events as well as between the pathways. Financial impacts and recovery tend to follow the severity pattern of the flood characteristics (i.e. the hydraulic impact variables shown in Table 2.2), particularly the water level, which is considered the most important variable that explains flood damage (e.g. Gerl et al., 2016; Vogel et al., 2018). Within each flood event, the stronger flood pathway, i.e. dike breaches and flash floods, show significantly higher values than their less severe counterparts (river and

Table 2.3: Financial flood impacts, perceived recovery and psychological burden reported by households affected by different flood pathways in 2013 and 2016

Subsample (Pathway)	River2013	↔	Dike2013	2013 ↔ 2016	Surface2016	↔	Flash2016	Overall
Sample size	1258	—	394	—	448	—	153	2253
Financial damage								
Mean financial damage to the building [EUR][1]	48,610.0	****	81,910.0	****	17,650.0	****	123,000.0	56,140.0
Mean financial damage to the contents [EUR][1]	16,220.0	****	27,830.0	****	12,350.0	****	47,400.0	20,700.0
Mean loss ratio of the building [%]	9.4	****	17.0	****	3.3	****	21.1	11.0
Mean loss ratio of the contents [%]	19.0	****	29.9	****	10.7	****	38.6	21.9
Perceived recovery AT THE TIME OF THE INTERVIEW, i.e. 8 to 10 months after the damaging flood event								
Mean loss compensation (payouts) [EUR][1]	10,810.0	****	18,200.0	****	16,680.0	****	33,110.0	14,320.0
Mean perceived status of repair works at the building [Likert-scale from 1 (building is completely restored) and 6 (there is still considerable damage)]	2.8	****	3.3	****	1.7	****	2.9	2.6
Mean perceived replacement of damaged household items [Likertscale from 1 (damaged household items are completely replaced) and 6 (still considerable missing household items)]	2.4	****	3.0	.	2.1	****	3.2	2.6
Mean perceived psychological burden [Likert-scale from 1 (no burden at all) to 6 (still heavy burden)]	3.4	****	4.0	****	2.6	****	3.7	3.3

Percentage or means only regarding valid values, i.e. answered entries.
[1] in 2016-prices
Comparison of subsets or 2013 to 2016 in the middle columns, with P-value ranges from Mann-Whitney-Wilcox or Chi-Square tests represented as: Legend: '****' ≤ 0.001 '***' ≤ 0.005 '**' ≤ 0.01 '*' ≤ 0.05 '.' ≤ 0.1 ' ' ≤ 1

surface water floods). This supports the hypothesis that the overall (hydraulic) severity of a flood pathway is more important for the perceived psychological burden than the general flood type (see Laudan et al., 2020). The results further support studies that recommend developing pathway-specific loss models (Mohor et al., 2020; Mohor et al., 2021; Vogel et al., 2018). At this point, the question arises whether and to which degree flood pathways also govern coping options.

2.4.4 Short-term response as coping strategy: warning and emergency measures

There are several strategies to mitigate flood impacts, of which 1) preparedness and response in the case of an event, 2) damage mitigation by implementing property-level adaptation measures and 3) risk transfer in terms of insurance coverage are the most relevant for residents (Driessen et al., 2016). The first strategy can also be described as reactive or short-term response, while the second is seen as a more proactive or long-term coping strategy (Neise & Revilla Diez, 2019). Insurance coverage does not primarily reduce damage, but facilitates a quick recovery since financial losses are compensated; its interlinkage with property-level adaptation is not clear (e.g. Hudson et al., 2017; Hudson et al., 2020; Surminski & Thieken, 2017). In this section, we focus on reactive responses, for which timely warning is an important pre-requisite (e.g. Penning-Rowsell & Green, 2000).

Table 2.4 reveals highly significant differences between the two flood events with regard to warning and emergency response. Residents affected by the 2013-flood were warned more often and at a considerably longer lead time in comparison to the 2016-event (Table 2.4). After the extreme flood event in 2002 in Germany, various initiatives and high investments had been undertaken to improve river flood risk management including early warning and preparedness, which had proven to be successful in 2013 (Kreibich, Müller et al., 2017; Thieken, Kienzler et al., 2016).

Table 2.5 provides more details on how people had become aware of the imminent flood danger underlining the huge differences between the two flood events. Considerably more residents who had been affected by the 2013-flood received official flood warnings than it was the case in 2016: while 31 to 55% of the people affected in 2013 were warned by severe weather warnings, flood alerts or calls for evacuation, this applies to just 3 to 14% of those affected in 2016 (Table 2.5). It is striking that own/independent observations play an important role in all four data subsets: one third to more than half of the people per subsample reported that their own observations of e.g. cloud formations, heavy rainfall or rising water levels made them aware of the imminent flood danger (Table 2.5). However, while just 4 to 6% of the 2013-flood victims were not warned at all, this applies to 26 to 36% of people surveyed in 2016 (Table 2.4 and 2.5).

These numbers reflect the current differences in the warning capabilities of river floods and convective storms or flash floods: while river floods, particularly at reaches downstream, can be forecasted several days in advance, forecasting convective storms that cause pluvial flooding is more challenging due to the dynamic formation of convective cells. Moreover, small creeks are often ungauged and not included in the regional flood monitoring and forecasting system of the federal state, but may unfold unexpected flash floods and inundations. Hence, lead times are restricted to a few hours, if at all (Merz et al., 2020). This is illustrated by the average lead time that is particularly short for the flash floods in 2016 (Table 2.4). The median values suggest that 50% of the people affected in 2013 were warned at least 24 hours before the water entered their home, while this value drops to just one hour for the 2016-subsets (Table 2.5), which contain maximum lead times of 24 hours in the surface water subset (20 cases from 14 different places) and maximum lead times of 12 hours in the flash flood subset (3 cases from 3 different places). For the pathway dike breach, which is characterized by stronger and unforeseen flooding, the mean lead time is significantly different from the mean value for river floods (Table 2.4), indicating that dike breaches pose an additional challenge on timely and informative warnings and hence time-critical situations may arise in the hinterland of dikes. The fact that the percentages of people who were not warned and – to a lesser degree the lead time – do not differ (highly) significantly between the flood pathways, but between the events underlines that warning possibilities and capacities are primarily governed by the overall flood type (fluvial versus pluvial) or the triggering atmospheric pattern, while knowledge and emergency response are additionally influenced by the pathway, particularly in 2013 (Table 2.4).

Residents affected by river floods in 2013 knew much better how to protect themselves from flooding than people affected in 2016 (Table 2.4). In addition, the values of the perceived response knowledge indicate highly significant differences within the event of 2013, suggesting that people affected by dike breaches had to cope not only with shorter lead times, but were more often unaware of what they could do to mitigate losses and protect their lives. Knowledge about adequate behaviour is, however, an important prerequisite for loss mitigation (Kreibich et al., 2021). Within the 2016-event differences are smaller, but indicate that people affected by flash flood were less informed/prepared (Table 2.4). In detail, the percentage of well-informed people who chose a 1 or 2 when asked how well they knew how to protect themselves and their household from flood impacts on a scale from 1 to 6, drops from 65% for river floods in 2013 to 48% in the subset containing dike breaches and even to 24% of cases with surface water flooding in 2016 and 15% for flash floods in 2016. This pattern indicates shortcomings in crisis and risk communication with respect to pluvial flooding in general and flash floods in particular, but it could also be influenced by previously experienced flooding and associated learning effects (see section 2.4.6).

Table 2.4: Characteristics of the warning process and emergency response as reported by households affected by different flood pathways in 2013 and 2016

Subsample (Pathway)	River2013	↔	Dike2013	2013 ↔ 2016	Surface2016	↔	Flash2016	Overall
Sample size	1258	—	394	—	448	—	153	2253
Households that received no warning [%]	6.3		4.3	****	35.5	*	25.5	13.1
Mean warning lead time [hours][1]	36.5	*	30.4	****	2.5		1.2	27.6
Mean perceived knowledge about self-protection [Likert scale from 1 (I knew exactly what to do) to 6 (I did not know at all what to do)]	2.4	****	3.1	****	4.3	*	4.8	3.1
Average number of performed emergency measures [count]	4.24	***	4.64	****	1.65		2.00	3.64

[1] Cases that received no warning were considered with a lead time of 0 hours.
Comparison of subsets or 2013 to 2016 in the middle columns, with P-value ranges from Mann-Whitney-Wilcox or Chi-Square tests represented as: Legend: '****' $\leq$ 0.001 '***' $\leq$ 0.005 '**' $\leq$ 0.01 '*' $\leq$ 0.05 '.' $\leq$ 0.1 ' ' $\leq$ 1

The different warning capabilities and the different levels of perceived response knowledge are further reflected in the responsive behaviour during the events: residents affected in 2013 undertook a significantly higher number of emergency measures namely around four or five, than those affected in 2016 with one or two measures on average, while there are no differences between pathways in 2016 (Table 2.4).

To get a clearer picture, Figure 2.3 shows what kind of emergency measures were undertaken. While residents affected by fluvial flooding in 2013 performed a variety of measures, residents affected in 2016 relied mostly on water pumps. Further, it should be noted that in the case of fluvial floods electricity and natural gas is more often switched off centrally, while those affected by pluvial floods have to take care of it on their own, which poses further risks of electrocution in case a person enters the water.

Overall, the analyses illustrate that residents in areas that are prone to river flooding were provided with better and timely warning information in 2013. Together with their higher level of response knowledge they were capable of performing more emergency measures than residents affected in 2016. Since emergency response seems to be an effective coping strategy for pluvial flooding, particularly due to their relative low water depths (Rözer et al., 2016; Spekkers et al., 2017), our analysis highlights that there is room for improving not only early warning, but also communicating potential measures and adequate behaviour in case of pluvial flooding in general. Table 2.4 and Figure 2.3 further reveal that residents affected by dike breaches tend to perform more emergency measures, although they have less knowledge and shorter lead times. The resulting damage (Table 2.3) shows that this strategy probably only mitigates a small amount of damage. Hence, more studies on the efficacy of emergency measures are needed.

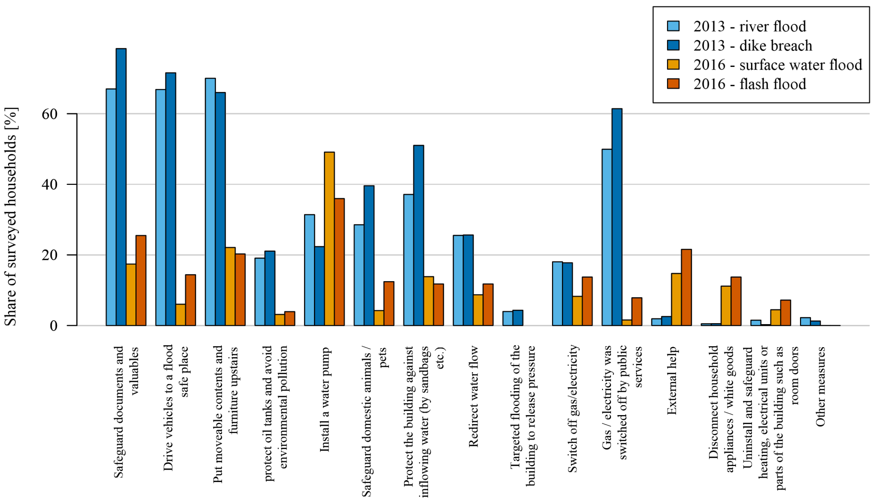

Figure 2.3: Performed emergency measures before and during the event as reported by households affected by different flood pathways in 2013 and 2016 (multiple answers possible)

Table 2.5: Answers to the question: “How did you become aware of the imminent danger of being flooded?” (multiple answers possible), given in percentage of all interviewed residents per subset and median lead time per subset

Subset	2013-river flood	2013-dike breach	2016-surface water flood	2016-strong flash flood
Severe weather warning (by DWD)	44.0%	31.0%	13.6%	9.2%
Severe weather warning (by other agencies)	—	—	3.3%	6.5%
Flood warning by authorities	44.7%	50.0%	—	—
Warning and evacuation at the same time	25.5%	54.8%	—	—
General media coverage	16.8%	18.5%	5.4%	1.3%
Warning by neighbours, friends etc.	17.7%	19.0%	7.6%	11.8%
Own independent search for information	27.8%	24.9%	2.0%	0.7%
Independent observations (e.g. water levels)	46.8%	35.3%	47.3%	55.6%
No awareness of the imminent hazard (no warning)	6.3%	4.3%	35.5%	25.5%
Not specified / no answer	1.0%	0.8%	1.8%	2.6%
Number of valid cases (warning source)	1258	394	448	153
Median of the lead time [hours]	24	24	1	1
Number of valid cases (lead time)	922	305	141	50

2.4.5 Long-term response as coping strategy: performance of property-level flood adaptation BEFORE and AFTER the floods

Besides emergency response in the case of an event, there are various proactive precautionary (or adaptive) measures that can reduce flood losses (e.g. Attems, Thaler, Genovese et al., 2020; Kreibich et al., 2015). Both surveys included questions on the actual and intended implementation of property-level flood adaptation. In particular, respondents were asked to state whether they had implemented a specific measure before or after the event, are planning to do so within the next six months or do not intend to implement that measure. In total, 16 measures were considered, four of which comprised informative measures (search for information about the flood risk or adaptation options, attendance of flood seminars or participation in neighbourhood networks). Another six measures addressed non-structural adaptation (flood-adapted building use, flood-adapted interiors and avoidance of noxious liquids in the cellar, e.g. petrol, paint), which also included measures that improve preparedness (purchase of a water pump or an emergency power generator or existence of an emergency plan and box). Insurance coverage was treated separately. Finally, the implementation of five structural measures was studied (i.e. relocating heating and electricity, securing heat and oil tanks, improving the flood safety of the building, installing a backflow preventer or water barriers); commonly, structural measures can be implemented by homeowners only.

In Table 2.6 the mean relative implementation per category is presented for the situation before the damaging flood and around nine months later. To calculate the relative implementation, the total count per category was normalized by the count of possible measures per category, i.e. a person who had implemented all five structural measures got the value 1, a person who had only secured the heat and oil tank and implemented a backflow preventer received 0.4 (2/5). The values in Table 2.6 correspond to the average relative implementation of the measures per category per subsample. It should be noted that only property owners were asked about the five structural measures.

Table 2.6 reveals that adaptive behaviour before the floods was significantly different between the two flood events. In all categories, i.e. informative, non-structural and structural measures, as well as insurance, people affected in 2013 were better adapted to the flood risk than residents affected in 2016. In most categories, the values for 2013 are around twice as high as in 2016. With regard to the different pathways, there are no differences in the 2016-cases, while in the 2013-samples there's a significant difference with regard to non-structural adaptation and a slight difference in structural adaptation. Hence, people affected by dike breaches in 2013 were less adapted than those affected by river floods (Table 2.6).

Table 2.6: Property-level adaptation before and after damaging floods as reported by households affected by different flood pathways in 2013 and 2016

Subsample (Pathway)	River2013	↔	Dike2013	2013 ↔ 2016	Surface2016	↔	Flash2016	Overall
Sample size	1258	—	394	—	448	—	153	2253
Property-level adaptation (long-term) – BEFORE the flood								
People who sought information about the flood hazard or protection options [%]	76.5	.	71.8	****	34.3		32.2	64.3
Of those without flood experience, people who sought information about the flood hazard or protection [%]	65.7		70.7	****	27.1		27.0	51.8
Mean relative implementation of 4 potential informational precautionary measures [%]	39.7		37.6	****	13.8		13.2	32.4
Mean relative implementation of 6 potential non-structural precautionary measures [%]	40.7	***	35.4	****	21.0		19.6	34.4
Mean relative implementation of 5 potential structural precautionary measures [%][1]	20.0	.	17.6	****	9.5		8.3	16.7
Households that took out insurance [%]	56.9		56.5	****	36.7		35.1	51.4
Property-level adaptation (long-term) – AFTER the flood								
Mean relative additional implementation of 4 potential informational precautionary measures [%]	9.1	****	14.8	****	21.3	****	35.3	14.3
Mean relative additional implementation of 6 potential non-structural precautionary measures [%]	7.6	****	12.1	****	15.8		17.9	10.7
Mean relative additional implementation of 5 potential structural precautionary measures [%][1]	5.6	**	7.9	****	14.9	.	19.1	8.8
Households that took out insurance after the flood [%]	4.7	***	9.1	****	12.4	****	27.7	8.6

Percentage or means only regarding valid values, i.e. answered entries.
[1] Only among homeowners
Comparison of subsets or 2013 to 2016 in the middle columns, with P-value ranges from Mann-Whitney-Wilcox or Chi-Square tests represented as: Legend: '****' $\leq$ 0.001 '***' $\leq$ 0.005 '**' $\leq$ 0.01 '*' $\leq$ 0.05 '.' $\leq$ 0.1 ' ' $\leq$ 1

After the flood, the adaptation status and the differences between and within flood events changed considerably revealing a pathway-specific behaviour. Table 2.6 confirms a boost of information-seeking behaviour in all subsets with, however, a varying degree: people affected by flash floods in 2016 searched most frequently for additional information on flood risk and mitigation options, followed by residents affected by surface water flooding in 2016, dike breaches in 2013 and river floods in 2013 (Table 2.6).

If we sum up the mean relative implementation of informational precaution before AND after the floods, people affected by dike breaches performed best (52% mean implementation), followed by river floods in 2013 and flash floods in 2016 (49% mean implementation each) and surface water floods in 2016 (just 35% mean implementation). This pattern persists when intended information-seeking behaviour is included (Figure 2.4) and illustrates that particularly severe flood pathways and impacts trigger information-seeking behaviour.

When it comes to the implementation of non-structural and structural measures or to the conclusion of an insurance policy, the additional mean implementation follows – in principle – a pattern similar to the information-seeking behaviour: residents affected in 2016 implemented the most additional measures, followed by those affected by dike breaches in 2013 and river floods in 2013 (Table 2.6). This might also be due to the fact, that more people affected by river floods in 2013 had already implemented measures before the flood, so the perceived necessity for further improvement after the flood was not as high as among residents affected in 2016.

Considering that the subgroups started at very different levels of adaptation before the events stroke, the cumulative implementation depicted in Figure 2.4 reveals that non-structural measures are more popular along rivers, i.e. among those affected in 2013. On average, a relative implementation of 50% of a total of six measures is reached, meaning that on average three measures have been implemented per affected household, in contrast to around 40% or 2.4 measures in the case of the 2016-subsamples (Figure 2.4b). Maybe this is due to a higher risk perception of fluvial floods in contrast to pluvial floods.

Interestingly, the cumulative implementation of structural adaptation measures reaches a similar level across all four flood pathways, though the overall lowest numbers in comparison to the other categories: around nine months after the floods a mean implementation of around 25% (or 1.3 measures) is reported in all four subsamples and inches up to 30% (or 1.5 measures) when intended adaptation is included (Figure 2.4c). This pattern was described before for fluvial floods (Kienzler et al., 2015; Thieken et al., 2007) and pluvial floods (Rözer et al., 2016), where structural measures such as sealing the basement, relocating heating or electrical utilities to higher stories or changing the heating system or protecting the oil tank had been identified as the least popular measures.

Most likely this is due to the higher costs of structural measures and the fact that the property-owner has to implement them.

The conclusion of insurance reflects the pattern of the information-seeking behaviour (Table 2.6, Figure 2.4d) and highlights that particularly people who experienced severe flood pathways strive for a backstop. In addition, the severity of the flood processes and their impacts might cause a lower appraisal of the efficacy of adaptive measures on the property-level. Therefore, the next section finally looks at perceptions.

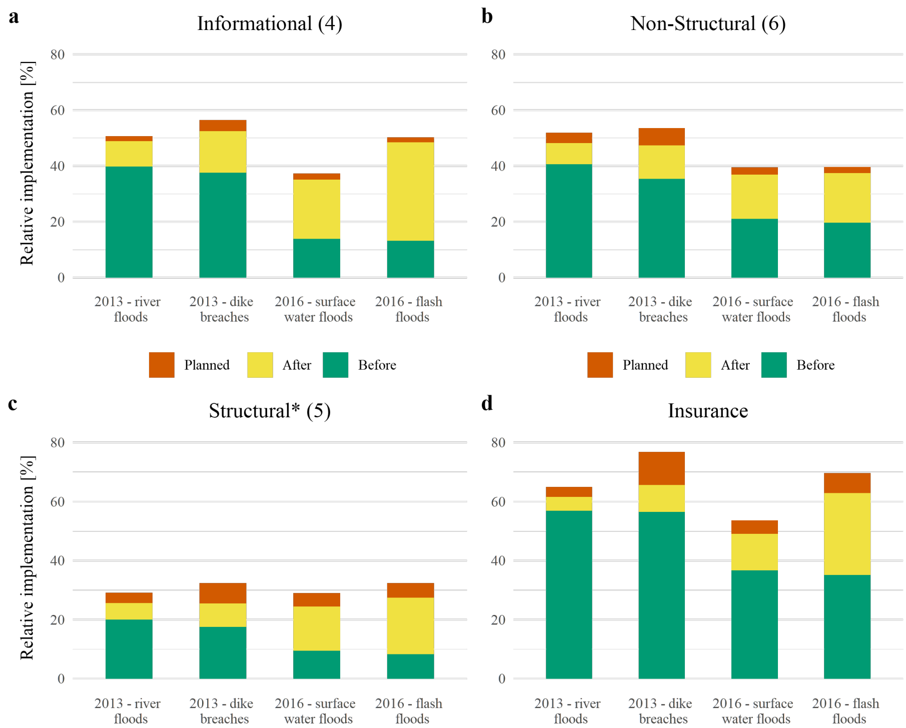

Figure 2.4: Cumulative mean relative implementation of adaptation, including measures that were (at the time of the survey) planned to be implemented within the next six months (* surveyed only among homeowners)

2.4.6 Previously experienced flooding and risk perceptions

Since previous flood experience impacts risk perceptions and influences adaptive behaviour (e.g. Bubeck et al., 2012), Table 2.7 summarizes related outcomes. There are significant differences with regard to previously experienced flooding between and within the events. Most households affected by river floods in 2013, i.e. 64%, had been affected previously. This percentage is much lower in the subset on dike breaches in 2013 (34%) as well as on surface water floods in 2016 (29%), and flash floods (only 21%; Table 2.7). As noted by Kienzler et al. (2015), having experienced river floods has considerably changed after the 2002-flood, whilst there is a lower percentage among those affected by pluvial floods, which was also observed by Spekkers et al. (2017), who reported that just 21%

of households surveyed in the city of Münster had been flooded before the severe pluvial flood of July 2014.

However, among all surveyed households, less than 15% had experienced a flood in the ten years preceding the events that are studied in this paper, with a distinction between the stronger pathways (8% for 2013-dike breach and 7% for the 2016-flash flood subsamples) and the low/medium flood pathways (16% for 2013-river and 17% for 2016-surface water flood subsamples, see Table 2.7). Altogether, residents that were affected by flash floods in 2016 were the least experienced with flooding. It is remarkable that the highly significant differences in previously experienced floods between the two events vanish when just the preceding ten years are taken into account, while the differences within the events, i.e. between the different pathways, remain (Table 2.7).

With regard to various perceptions, it is striking that there are no to just small differences between the events and the pathways with regard to perceived self-efficacy and the perceived responsibility of the government (Table 2.7). A comparison with other regions and data could reveal whether the reported values could be regarded as representative mean perception or as a kind of benchmark. Particularly, self-efficacy is seen as a key component for adaptive behaviour (Bubeck et al., 2013; Poussin et al., 2014) and tends to be lower with regard to flash floods (Table 2.7), which might be accompanied by heavy structural damage (Laudan et al., 2017).

Average perceived response costs, response efficacy and responsibility of any individual to reduce damage, however, differ between the two events: people affected in 2013 perceived response costs a bit higher than those affected in 2016; this also holds for the perceived efficacy of measures and the responsibility of individuals (Table 2.7). It is striking that response efficacy is perceived the lowest by people who were affected by flash floods in 2016, probably highlighting the high velocities and severe impacts on buildings (Table 2.2 and 2.3) and indicating the limits of property-level adaptation.

Table 2.7: Previously experienced flooding and perceptions on risk and property-level adaptation of households affected by different flood pathways in 2013 and 2016

Subsample (Pathway)	River2013	↔	Dike2013	2013 ↔ 2016	Surface2016	↔	Flash2016	Overall
Sample size	1258	—	394	—	448	—	153	2253
Previously experienced flooding								
People who experienced at least one previous flood [%]	63.9	****	33.7	****	29.1	.	21.3	48.6
People who experienced a flood in the ten years preceding the damaging event [%]	16.4	****	7.5		16.8	**	7.3	14.3
Perceptions – AFTER the flood								
Mean perceived probability of future floods [Likert-scale from 1 (it is very UNlikely that I will be affected by future floods) to 6 (it is very likely that I will be affected by future floods)]	4.6	****	3.8	****	3.7	***	3.2	4.2
Mean perception of impacts of a future flood LIKE THIS ONE [agreement to the statement "It won't be as bad as in 2013/16" 1: I fully agree to 6: I fully disagree]	4.1	****	3.6	.	4.1	****	3.2	3.9
Mean perceived self-efficacy [agreement to the statement "Personally, I am UNable to implement any of the proposed precautionary measures" 1: I fully agree to 6: I fully disagree]	4.3		4.2		4.5	**	4.0	4.3
Mean perceived costs [agreement to the statement "Private precautionary measures are too expensive" 1: I fully agree to 6: I fully disagree]	2.9		2.9	***	3.3	*	2.9	3.0

Previously experienced flooding and perceptions on risk and property-level adaptation of households affected by different flood pathways in 2013 and 2016 (continued)

Subsample (Pathway)	River2013	↔	Dike2013	2013 ↔ 2016	Surface2016	↔	Flash2016	Overall
Mean perceived response efficacy [agreement to the statement "Private precautionary measures can considerably reduce damage" 1: I fully agree to 6: I fully disagree]	2.6	.	2.8	***	2.7	****	3.3	2.7
Mean perceived responsibility of the government [agreement to the statement "Flood risk reduction is a task of the government, not of the residents" 1: I fully agree to 6: I fully disagree]	3.0	*	2.8	.	3.1		2.9	3.0
Mean perceived responsibility of individuals [agreement to the statement "Everyone is obliged to reduce flood damage as much as possible" 1: I fully agree to 6: I fully disagree]	1.7	*	1.9	****	2.4		2.5	1.9

Percentage or means only regarding valid values, i.e. answered entries.

[1] Only among the homeowners

Comparison of subsets or 2013 to 2016 in the middle columns, with P-value ranges from Mann-Whitney-Wilcox or Chi-Square tests represented as: Legend: '****' $\leq$ 0.001 '***' $\leq$ 0.005 '**' $\leq$ 0.01 '*' $\leq$ 0.05 '.' $\leq$ 0.1 ' ' $\leq$ 1

Furthermore, the threat appraisal of future floods differs significantly between and within the events: the perceived probability of future floods is the highest among residents affected by river floods in 2013, followed by dike breaches in 2013 and surface water flooding in 2016. Those who were affected by flash floods in 2016 tend to believe that they will not be affected again. This pattern is even more pronounced when a statement on the perception of the impacts of a future flood LIKE THIS ONE was assessed: here the ones who were damaged the most (i.e. by flash floods in 2016 and by dike breaches in 2013, see Table 2.3) tend to think that impacts comparable to the just experienced are less likely to occur (Table 2.7). This highlights that it is important to distinguish probability and impacts in threat appraisals as shown by Bubeck et al. (2013). The statement on the perceived impacts of future floods also contains a nuance of denial of the flood risk, which might explain the lower adaptation that is revealed in Figure 2.4.

2.5 Conclusions

Based on two surveys among residents in Germany who were affected by flooding in 2013 and 2016, respectively, this paper looked at differences in flood processes, impacts and coping strategies between four flood pathways found in these spatially compound inland flood events. While the socio-economic characteristics did not differ much between the samples (except for income, which can be explained by the spatial patterns of the floods), impacts and coping strategies differed considerably. Based on the detailed quantitative analyses of a broad range of variables presented in section 2.4, each flood pathway can be characterized qualitatively as shown in Table 2.8. The following event-based storylines were derived from these findings and can be applied to environments similar to the studied regions.

River floods (2013): The flood processes are characterized by high water levels and long durations of inundations. The financial impacts, recovery and the psychological burden from the flood represent more or less the average of the total data (note that this was the biggest subsample). Most of the residents affected by river floods in 2013 were warned in advance with comparatively long lead times. They were well-prepared, i.e. performed many emergency measures and also showed the highest level of flood adaptation at their property before the flood hit. After the flood they undertook considerable additional adaptation, but Figure 2.4 reveals that they lost their top position and other subsamples reached the same level, although this group believes on average to be affected again by future floods and also agrees that individuals have to contribute to flood risk reduction. Overall, adaptation of this group could be supported by financial incentives and funds since they perceive response costs as rather high (Table 2.7). Such costs might also be related to the efforts involved to implement a measure. Therefore, improved consultation and support during implementation as also proposed by Attems, Thaler, Snel et al.

Table 2.8: Qualitative summary of the flood pathway characteristics, where medium often reflects the averages

Characteristics	Flood pathways			
	river flood 2013	dike breach 2013	surface water flood 2016	flash flood 2016
Hydraulic flood characteristics	MEDIUM	HIGH	SMALL	HIGH
Financial impacts	MEDIUM	HIGH	SMALL	HIGH
Perceived recovery	MEDIUM	BAD	GOOD	BAD
Warning and emergency response	GOOD	MEDIUM	BAD	BAD
Property-level adaptation before	GOOD	GOOD	BAD	BAD
Property-level adaptation after	MEDIUM	GOOD	BAD	MEDIUM
Flood experience	HIGH	MEDIUM	MEDIUM	LOW
Risk and responsibility perception	MEDIUM	MEDIUM	MEDIUM	LOW

(2020) deserve further attention. Since previously experienced flooding was the highest in this subsample, their level of adaptation after the flood might also indicate a kind of saturation level. This hypothesis, however, needs to be researched in more detail.

Dike breaches (2013): This pathway is characterized by very high water levels, very long durations of inundations and a high frequency of oil contamination. Consequently, the financial impacts are the second highest, repair works at buildings are slow and the psychological burden from the flood is the highest across all four sub-samples. Most of the residents affected by dike breaches in 2013 were warned in advance with comparatively long lead times. Like those that were affected by river flooding, they performed many emergency measures and showed to be comparatively well-informed about flood hazards and coping options. With regard to structural and non-structural measures, adaptation before the flood was lower than in the river-flood-sample, but they reached a similar level after the flood and a higher level of insurance penetration. Perceptions of flood risk, coping options and responsibilities represent more or less an average behaviour. The fact that losses are very high despite a good responsive and adaptive behaviour indicates the limits of individual adaptation in view of the high hydraulic impacts caused by dike breaches. Insurance serves as a backstop. Overall, this group should be further educated with regard to risks and suitable coping options. Since response time might be limited in case of dike breaches, potential environmental risks due to bursting oil tanks or the release of other harmful substances should receive particular attention. During the last revision of the German Federal Water Act a regulation of oil tanks in (potentially) flood-prone areas was already introduce. Still, more information on effective and suitable property-level adaptation is needed for residents potentially affected by this flood pathway.

Surface water floods (2016): The flood processes are characterized by (very) low water levels and short durations of inundations. Financial impacts and psychological burden from this pathway were the lowest across the sub-samples, while there was a speedy recovery. Threats may occur from high velocities. Most of the residents affected by surface water flooding in 2016 were not warned in advance, lead times were short and knowledge about self-protection was below average. Hence, people prone to pluvial flooding – this is in general the urban population, since pluvial floods are ubiquitous – should be better informed about potential traps (cellars, subways, cars etc.) and suitable adaptation measures, particularly after events. In comparison to other sub-samples, this group was the least informed and the least insured. Moreover, implementation of non-structural measures was below average – also after the event. Therefore, risk communication on pluvial flooding has in general to be improved and has a good chance to be successful since threat and coping appraisals are well developed and the uptake of measures after the 2016-event was good. Responsibility and feasibility should be clearly communicated and demonstrated by best practise examples. Workshops could serve as a good instrument in this case as they strengthen self-efficacy and protection motivation (Heidenreich et al., 2020).

Flash floods (2016): The flood processes are characterized by (very) high water levels and often (very) high flow velocities which might be accompanied by contamination. These dynamic processes led to the highest financial impacts and a high psychological burden. Recovery was comparable to the dike-breach-sample of 2013, although this group received the highest financial support which might be due to the lumped character of this subsample with cases from just ten municipalities. Like other affected residents in 2016, most of the people in this group were not warned in advance, and if so, lead times were short. Due to potential danger to life caused by flash floods, local forecasting and warning systems should be installed. The preparedness and adaptation before the flood in the subsample is comparable to the surface-water-flood-2016-group. After the flood the information-seeking behaviour was very high, as was the conclusion of insurance policies that serve as a backstop. To strengthen property-level adaptation, risk communication should focus on the efficacy of measures that can also withstand high flow velocities.

Altogether, the study demonstrates that flood hazard characteristics, impacts and coping options differ between and also within compound inland flood events. Hydraulic characteristics and flood impacts are strongly governed by the specific flood pathway, while coping options (short and long term) are more related to the general flood type (i.e., fluvial and pluvial). Hence, the concept of spatially compound events is helpful to understand different flood impacts, but could be strengthened towards coping and adaptive behaviour. The above-mentioned flood pathway-specific recommendations for risk communication and management are a first step in this direction. In addition, we can draw some conclusions that go beyond the studied cases and the German context.

First, the relation between hydraulic forces and impacts strongly support recommendations of developing pathway-specific loss models as done by Mohor et al. (2020), Mohor et al. (2021) and Vogel et al. (2018). Research on this is, however, in its infancy. Secondly, to further mitigate damage, risk and crisis communication should distinguish not only flood types, but also pathways highlighting their specific threats, e.g. life-threatening situations during flash floods. Identifying and communicating such threats might better fulfil user needs, as it has been shown that adding impact information or additional descriptions of the threats may provide a clearer picture of the upcoming situation than abstract indications of warning levels (e.g. “strong”), specially to less proficient users (Kox et al., 2018). With regard to flash floods options for local warning and alerting systems should be explored as an option of improving warning and response in small catchments.

Thirdly, it should be noted that experiencing strong flooding caused by dike breaches or flash floods boost precaution, while surface water flooding does not, although the latter can happen almost everywhere. Therefore, modes to communicate and experience flood impacts in a tangible way are particularly important (e.g. exhibitions, storytelling etc.). In addition, the efficacy of emergency and precautionary measures with regard to different pathways needs further research. Finally, people affected by strong pathways such as dike breaches or flash floods (with sediment loads) need special assistance to recover physically and mentally from the impacts; their burden is the highest. Our results indicate that these residents experience limits of their adaptation options.

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Chapter 3

A Comparison of Factors Driving Flood Losses in Households Affected by Different Flood Types [1]

Abstract Flood loss data collection and modeling are not standardized, and previous work has indicated that losses from different flood types (e.g. riverine, groundwater) may follow different driving forces. However, different flood types may occur within a single flood event, which is known as a compound flood event. Therefore, we aimed to identify statistical similarities between loss-driving factors across flood types and test whether the corresponding losses should be modeled separately. In this study, we used empirical data from 4418 respondents from four survey campaigns studying households in Germany that experienced flooding. These surveys sought to investigate several features of the impact process (hazard, socioeconomic, preparedness, and building characteristics, as well as flood type). While the level of most of these features differed across flood type subsamples (e.g. degree of preparedness), they did so in a nonregular pattern. A variable selection process indicates that besides hazard and building characteristics, information on property-level preparedness was also selected as a relevant predictor of the loss ratio. These variables represent information which is rarely adopted in loss modeling. Models shall be refined with further data collection and other statistical methods. To save costs, data collection efforts should be steered towards the most relevant predictors to enhance data availability and increase the statistical power of results. Understanding that losses from different flood types are driven by different factors is a crucial step towards targeted data collection

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and model development, and will finally clarify conditions that allow us to transfer loss models in space and time.

3.1 Introduction

Natural hazards have a large economic impact on human society. In Europe, for instance, natural hazards caused almost €557 billion in damages between 1980 and 2017 (European Environment Agency, 2019). Floods tend to account for a prominent share of these losses. For example, Germany has frequently been hit by large-scale floods; since 2002, there have been eight floods which have, individually, inflicted a monetary loss of more than €100 million (Kienzler et al., 2015; Natho & Thieken, 2018; Surminski & Thieken, 2017). The 2002 event caused the largest monetary loss, amounting to €11.6 billion according to 2002 prices (Thieken et al., 2006).

Due to the magnitude of these impacts, a great deal of effort has been invested in developing methods for estimating flood losses. This has resulted in a wide range of methods being currently employed (Gerl et al., 2016; Merz et al., 2010; Meyer et al., 2013). However, the current approaches to loss estimation are limited by or face problems due to gaps in loss reporting. Loss reporting is the process of documenting and reporting the observed impacts of a flood event. The quality and consistency of loss reporting is important because these data are used to train and validate loss estimates. However, despite this importance, the patchy, unstandardized, and heterogeneous nature of current loss documentation and reporting after events results in a degree of uncertainty in loss estimation (Downton & Pielke Jr, 2005; Handmer, 2003; Thieken, Bessel et al., 2016). Besides the loss reporting process, there is also a great deal of heterogeneity among the reported losses themselves (for example, see Fuchs, Keiler et al. (2019), Merz et al. (2004) and Thieken et al. (2005)). If reported data are to be used for deriving or training loss models, then it is essential to link the (financial) impact to characteristics of the hydraulic load and the affected structure. In this context, it is also important to investigate, determine, and order the importance of different variables as a part of the loss-generating process, which is likely to depend on the flood type (Kelman & Spence, 2004; Kreibich & Dimitrova, 2010). This knowledge and understanding, across flood types, can be used to increase the comparability of studies and filter back into improved documentation, creating a positive reinforcement effect.

The problem of understanding how flood losses are generated is important because flood loss modeling and estimation supports the planning of relief funds, insurance mechanisms, evaluation of risk mitigation strategies, and policy development (Merz et al., 2010; Meyer et al., 2013; Molinari et al., 2019). Moreover, numerical modeling is not only a tool for prediction, but also “a learning process” in which hypotheses can be tested or dismissed (Beven, 2007a; Hrachowitz et al., 2013). Ultimately, a better understanding of the drivers and mechanisms of flood loss can help to reduce risk through better risk management (Meyer et al., 2013), creating a positive feedback loop between data collection and modeling (Molinari et al., 2017; Molinari et al., 2019).

The development of flood loss models can be empirical or synthetic (Merz et al., 2010), although some methods accommodate a mix of expert input and data-driven processes (Penning-Rowsell et al., 2013; Schröter et al., 2014). Gerl et al. (2016) have reviewed 47 diverse approaches to flood loss modeling worldwide, 49% of which are purely empirically driven, while an additional 32% are a combination of synthetic and empirical approaches. It has been suggested that empirical models, although dependent on high-quality data, can achieve better accuracy by taking into account intervening factors, which are more difficult to include in synthetic model processes (Merz et al., 2010). Moreover, there is also the possibility that they can be updated with data from new events. Wagenaar et al. (2018) found that once a model calibrated with a narrow data set was updated to include a broader range of data, its performance improved when applied to a different region. This improvement was a reflection of the range of data used in model calibration. Moreover, comparative studies such as by Figueiredo et al. (2018) and Schröter et al. (2014) show that even among places with similar socioeconomic conditions, the success of model transferability is not straightforward or well understood.

It is also worth noting that in some countries the task of loss modeling has been standardized or one model is broadly applied (Australian Institute for Disaster Resilience, 2002; Olesen et al., 2017), such as FEMA's HAZUS-MH for the US (Federal Emergency Management Agency, 2013), the Multi-Coloured Manual for the UK (Penning-Rowsell et al., 2013), and the RAM and ANUFlood for Australia (Australian Institute for Disaster Resilience, 2002; Hasanzadeh Nafari et al., 2016). These models are a combination of data (empirical) and expert judgment (synthetic) (Gerl et al., 2016). The primary purpose of this standardization is not to improve the quality of the model per se, but to improve the comparability of studies due to using the same model or overall approach. However, other countries, including Germany, have not agreed upon a standard procedure for flood loss estimation, although several efforts are under development (Zeisler & Pflügner, 2019; Zeug et al., 2019), mainly models used by researchers, such as the ones used by Schröter et al. (2014) and cited therein. One exception is the HOWAD-Model (Neubert et al., 2016), which is preferred by some water authorities for project appraisals in specific regions of Germany. Focusing on Germany, some of the events considered by Schröter et al. (2014) are known to have presented different flood types. These different flood types tend to display important differences in the characteristics which are expected to play a role in the flood loss generating process. Given how different models have been developed for various flood types, one should note that in a single event, different flood types can occur at the same time, even in the same city or region (e.g. in Dresden in 2002, see Kreibich, Petrow et al., 2005). We refer to this phenomenon as a compound flooding event, inspired by definitions and examples presented by Zscheischler et al. (2018). The presence of compound events in the current practice of loss modeling is potentially problematic, because current flood loss modeling has heavily focused on river floods. The review by Gerl et al. (2016) revealed that only 6% of the 47 loss models investigated levee breaches, and only 4% rising groundwater, and none flash or pluvial floods. This strong focus on riverine floods is problematic if different flood types, e.g. inundations from rivers or after levee breaches, produce sufficiently different loss-generating processes during the same event. These flood types, or the combination of flood types within and across events, however, has not been explicitly included in current loss-modeling frameworks to the best of our knowledge. Therefore, despite the presence of compound floods and the existence of different flood models, we see that there is little overlap between flood types in how losses are assessed, implying that flood events are assessed with a single overall loss model. Fuchs, Keiler et al. (2019), for instance, found that subtypes are present, although such subtypes were not included in their model, similarly to Thieken et al. (2008). Therefore, it is possible that failure to act upon this will reduce the accuracy and robustness of loss estimation.

In order to study the generation of flood losses in Germany, a broad database addressing impacting flood events between 2002 and 2013 was constructed through computer-aided telephone surveys (Thieken et al., 2017; Vogel et al., 2018). This comprehensive dataset contains features that are rarely found elsewhere. From this data, we could attribute each respondent's experience to a given flood type. The collected data show that during the respective events, compound events did take place, with several flood types being observed in the same city, for example. The employed dataset or parts of it has been well used in flood loss estimation (Kreibich et al., 2010; Merz et al., 2013; Thieken et al., 2008; Vogel et al., 2014; Vogel et al., 2018). Despite the widespread approaches, the degree of transferability in space and/or time, i.e. the application of the model to a different event, is still limited (Cammerer et al., 2013; Schröter et al., 2014). In addition, the question of different flood types was only addressed by Vogel et al. (2018), where it was in fact identified as an important input towards loss assessment. However, in comparison to their study, in this study further variables are introduced, a different methodology is employed, and we quantify the order of importance of the identified predictor variables.

In this study, we address flood loss model transferability across four different flood types, i.e., fluvial flooding, pluvial flooding, groundwater flooding, and inundation caused by levee breaches, by investigating the loss-generating process for these flood types. For this, we present a two-step analysis. The first step is a univariate exploratory analysis of the available data in order to identify the most important potential predictors for the further development of flood loss modeling. The second stage advances upon stage one by employing a variable selection process linked to a series of linear regression models across flood types. This stage directly investigates how the loss-generating processes differ across flood types. Our results provide an indication of the transferability of flood loss models. For instance, if different flood types result in significantly different loss-generating processes, then different loss models may have to be nested within one another rather than relying on a single modeling approach. Additionally, we were able to indicate the order of importance regarding the identified variables, supporting the prioritization of data collection. From these analyses, we derive recommendations for future model development and related research.

3.2 Materials and Methods

3.2.1 Database

In order to reconstruct how different flood types cause a monetary loss at the property level, flood loss assessment must rely on data, either from measurements (either directly observed, or via experimentation or surveys of those directly affected) or from expert judgment. In order to collect widespread information on flood losses that occurred in the wake of widespread flood events, survey data from those directly affected are the most suitable choice. To this end, a dataset was constructed from surveys conducted via computer-aided telephone interviews (CATI; Thieken et al. (2017)) in the aftermath of large flooding events in 2002, 2005, 2006, 2010, 2011, and 2013 in Germany (Table 3.1). The motivation behind these surveys was to better understand the direct impacts suffered by those affected (Thieken et al., 2017). The surveys covered a range of topics, from hazard characteristics to preparedness, aimed at developing flood loss models and forensic analyses (Kreibich, Thieken, Haubrock et al., 2017), and had been previously presented e.g. in Kienzler et al. (2015), Thieken, Bessel et al. (2016), Thieken et al. (2007) and Thieken et al. (2005), Vogel et al. (2018). Each survey underwent adaptations for the sake of better clarity for respondents but maintained comparability over time. Therefore, this study can be considered to use repeated cross-sectional data.

To contact the affected households, press releases and flood maps were intersected with streets and telephone numbers from public address directories (Kienzler et al., 2015). Only households that had undergone some level of loss to the building or its contents were interviewed. According to Kienzler et al. (2015), it is likely that the most affected individuals, i.e. residents with destroyed homes, could not be reached. However, this source of bias is likely to be small (Thieken et al., 2010). We further reduce this bias by focusing on respondents who did not suffer a complete loss. A further discussion on potential sample bias is found in Kienzler et al. (2015).

Table 3.1: Number of interviewed households in time and space per flood type

Flood Type	Levee breach n=810	Riverine n=2509	Surface water n=447	Ground water n=652	Total n=4418*
Year					
2002	302	796	258	329	1685
2005	23	200	27	52	302
2006	2	133	10	11	156
2010	86	262	67	18	433
2011	3	158	16	37	214
2013	394	960	69	205	1628
Federal State					
Brandenburg	0	5	0	0	5
Saxony	389	1134	158	209	1890
Schleswig-Holstein	1	15	1	0	17
Saxony-Anhalt	218	428	70	170	886
Thuringia	27	144	9	32	212
Lower Saxony	5	96	47	30	178
Hesse	0	5	2	0	7
Rhineland Palatinate	1	47	9	7	64
Baden-Wurttemberg	0	54	6	5	65
Bavaria	169	574	143	197	1083

* Out of the complete database, 50 observations were not assigned to a flood type and thus removed

In Table 3.1 we present the number of surveyed data points as assigned to a particular flood type. In the 2002 survey, the responses were assigned to flood types according to how the water entered the house as reported by the respondent, the topography, and the proximity of the house to a river or levee. More than one flood type could have taken place on the same property. However, the one considered to be the most damaging was taken as representative of the respondent's experience. Still based on the 2002 data, the order, from most to least damaging flood type, was set as follows: levee breaches, riverine floods, surface water floods, and rising groundwater floods, after statistical analysis of all cases (Hristova, 2007). In the following events (i.e. after 2002), the flood type was assigned based on what the respondents attributed flooding on their property to, and the most damaging type was established if more than one type could be assigned. In the process of assigning flood types, the riverine and surface water flood types were more difficult to separate, compared to groundwater- or levee breach-affected households. While our database included data from six different years, there was a dominance of observations from the largest events in 2002 and 2013. Twelve out of the sixteen federal states in Germany were represented in the database. However, there was a dominance of data from Saxony, Bavaria, and Saxony-Anhalt, reflecting the most affected states, while some states had very few observations (e.g. Brandenburg, Table 3.1).

The surveys addressed several aspects of the flood events: characteristics of the affected building, the presence and characteristics of the warning as perceived by the surveyed residents, their flood experience and preparedness, socioeconomic information of the household, demographic information of the household, the hazard intensity at the property, and the losses to the building and its contents. The dataset was diverse not only in its aspects, but also in the format of answers, with continuous (metric), ordered, and nominal (nonmetric) scales – 12, 11, and 8 potential predictors, respectively. Ordered variables were treated as continuous variables since the Likert-scales only verbally expressed the meaning of the end points, not of the intermediate steps. These predictors were selected from the larger database after previous analyses indicated them as factors influencing direct monetary loss (Kreibich et al., 2011; Merz et al., 2013; Thieken et al., 2005; Thieken et al., 2008; Vogel et al., 2018), and with a reasonable balance between different aspects – hazard, preparedness, and building and socioeconomic characteristics, with the addition of administrative regions within Germany. We can reasonably group the variables as shown in Table 3.2.

Most of the surveys were completed around ten months after the flood. One of the reasons for not surveying directly after the event is to allow the respondents to recover and become fully aware of the repair costs involved. In addition, a later survey is more likely to capture second-order effects, e.g. in the case of oil contamination. This provides a more complete view of the damage and the involved repair costs.

3.2.2 Methods

The key objective of this study is to investigate whether different flood types display distinct loss-generating processes. Significant differences in which variables may be important, as well as their magnitude of importance, can indicate that different flood types should be treated differently in loss estimation and modeling. This importance could grow with better documentation indicating the presence of compound events within a single flood event. The dataset presented in the previous section is broad enough to study this topic. However, the analysis of loss-generating processes is complicated by possible dependence among the predictors as well as the range of scales present (e.g. metric, nonmetric, and metric response).

In order to address this complexity, we divide our analysis and approach into two stages (Figure 3.1). The first set is a series of preliminary tests based on univariate assessments. The purpose of the univariate assessments is to investigate the suitability of the linear regression assumptions and to compare the homogeneity of subsamples across flood types by investigating possible predictors individually. This step focuses on and guides our attention to suitable methods and variables for the second step of the analysis.

The second step of the analysis is the employment of a regression model framework to infer possible relationships between important variables and the building loss ratio. A multivariable regression is selected, as it is capable of accommodating several independent variables of multiple formats (metric and nonmetric) and one metric dependent

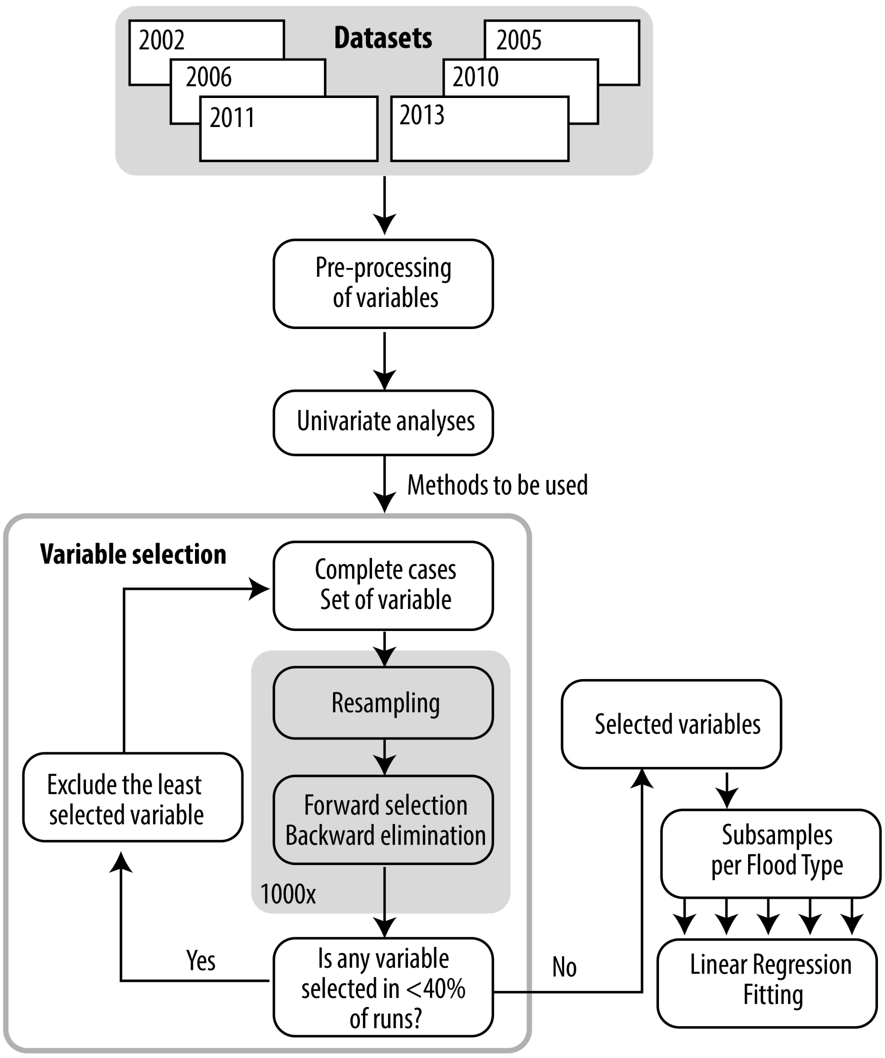

Figure 3.1: Sequence of analyses employed in this study

Table 3.2: Variables used in the study grouped by aspect (adapted from Vogel et al., 2018)

Variable	Description	Range and reference	Type[3]
Hazard characteristics			
Water depth	Relative to ground level	-248 to 1328 cm	C
Duration*	Duration of how long flood water was inside the house	1 to 1440 h	C
Velocity	Rank scale of flow velocity: 0 = no flow to 6 = very high velocity	0 – 6	O
Contamination	Indicator of contamination in the flood water: 0 = no contamination to 2 = heavy contamination (e.g. by oil)	0 – 2	O
Warning			
(Early) warning lead time*	Time between the warning and being hit by the water	0 to 336 h	C
Perceived knowledge about self-protection (quality of warning)	Rank scale: 1 = knew exactly what to do to 6 = didn't know what to do	0 – 6	O
Warning information	Indicator of information provided in the warning messages assessed with regard to supporting loss mitigation (Thieken et al., 2005)	0 to 16	O
Warning source	Indicator of source warning: 0 = no warning to 4 = warning from official agency (Thieken et al., 2005)	0 to 4	N
Gap warning-action	Gap time between receiving the warning and starting to act	0 to 336h	C
Preparedness			
Emergency measures	Indicator weighting emergency measures performed effectively (Thieken et al., 2005)	0 to 17	O
Precautionary measures	Indicator of overall precaution at the property with 0 = no precaution to 2 = very good precaution (Thieken et al., 2008)	0 to 2	O
Perceived efficiency of precautionary measures	Rank scale: 1 = measures could reduce loss efficiently to 6 = measures could not reduce loss at all	1 - 6	O

Variables used in the study grouped by aspect (continued)

Variable	Description	Range and reference	Type[3]
Flood experience class	Indicator of previously experienced floods with 0 = no previous experience to 4= recent and/or repeated experience (Thieken et al., 2005)	0 to 4	O
Awareness of flood risk	Knowledge that the residence was located in a flood-prone area	yes or no	N
Insurance cover	Flood insurance coverage before the event	yes or no	N
Building characteristics			
Ownership	Categorized: owner of the building, owner of the flat, or tenant	3 classes	N
Building type	Categorized: detached home, semi-detached home, or apartment building (with several flats)	3 classes	N
Number of flats	Number of flats in the building	1 to 40	C
Building quality	Rank scale: 1 = very high quality to 6 = very low quality	1 - 6	O
Building value[*,1]	Asset value inferred through standardized insurance practices	98.5 10^3 to 21.2 10^6 €	C
House or flat area[*]	Inhabitable area of the house or flat	20 to 1200 m^2	C
Building area[*]	Floor space of the whole building	32 to 18,000 m^2	C
Cellar	Presence of a cellar	yes or no	N
Household and socio-economic features			
Age	Age of the interviewed person	16 to 99 years old	C
Household size	Household size	1 to 20 persons	C
Children	Number of household members under 14 years old	0 to 6	C
Elderly	Number of household members over 65 years old	0 to 9	C
Income class	Categorized: from 11 = "> 500 Euros" to 16 = "3,000 Euros and up"	11 - 16	O
Socio-economic status	Categorized: 1 = lower class to 4 = upper class (Plapp, 2003 apud Thieken et al. (2005))	1 - 4	O

Variables used in the study grouped by aspect (continued)

Variable	Description	Range and reference	Type[3]
Others			
Region[2]	Grouping of federal states (see footnote 2)	3 classes	N
Year	Year of the event	2002, 2005, 2006, 2010, 2011, 2013	N
Loss (ratio)			
Building loss	Reported losses to the building (adjusted to 2013 prices)	0 to 1.1 10^6 €	C
Building loss ratio	Ratio between absolute monetary loss and estimated building value	0 to 100%	C

[*] Variable was log-transformed for the regression framework due to a high skew and its values are strictly greater than zero.

[1] Building values were estimated through standardized values leading to a high correlation with the building area and, therefore, this variable was dismissed.

[2] The German Federal States were grouped into three regions: 1 South (Bavaria and Baden-Wurttemberg – Danube and Rhine river basins); 2 former East German states; 3 North and West (e.g. Rhine, Ems, Weser, lower Elbe river basins).

[3] C – Continuous; O - Ordered; N - Nominal. For some ordered variables only the endpoints were given, so the variables can be considered as an interval scale. Ordered variables are treated as continuous.

variable, and can be used for both prediction and explanatory purposes (Hair et al., 2019). The regression framework first employs a variable selection process, to refine the set of explanatory variables to be included in the regression models. After completing the variable selection process, we fit several linear regressions concerning the different flood types in order to assess the potential for significant differences in the loss-generating process. Taken together, the variable selection process narrows our focus to the most important variables, and the linear regression helps to establish their relative power in explaining the loss ratio across different flood types. From this information, we can draw inferences on the suitability of adapting flood loss modeling to a specific or a combination of flood types present in a flooding event.

3.2.2.1 Univariate Assessments (Stage 1)

In order to choose the appropriate methods, we assessed the normality and variance of variables. All tests for univariate normality included in R's 'nortest' package (Gross & Ligges, 2015) were violated for all selected variables. Also, a 'visual representation' was performed using a QQ Plot (quantile-quantile plot to observe departure of an observed distribution from a theoretical distribution) of the Mahalanobis distance (distance of an observation from the center of a multivariate space), and tests composed for multivariate normality (included in R's 'MNV' package (Korkmaz et al., 2014)) were violated for the set of potential predictors. Therefore, all following tests should be reasonably robust against nonnormality.

With Levene's test (considered robust against nonnormality [Borcard et al., 2018]), we compared the variance of one variable at a time across the four groups (i.e. subsamples of households affected by each flood type), of which several variables presented heteroscedasticity, with the exception of: emergency measures, building quality, building value, household size, number of elderlies, and income class, only. The Box's M test for multivariate homogeneity of variance-covariance resulted in very low p-values, but the test is known to be sensitive to nonnormality, therefore its results might not have actually evaluated 'variance-covariance' but presented an already biased value for nonnormality (Friendly, 2018).

Focusing on the flood types, we assessed the homogeneity of the flood type subsamples. This is because a high degree of homogeneity would provide an initial indication that the loss-generating processes of the different flood types are similar. Additionally, a high degree of homogeneity would in turn support the transferability of flood loss models across different flood types. Due to the abovementioned nonnormality, the assessment of homogeneity across flood types was undertaken through the Kruskal-Wallis test, which is robust against nonnormality (Field et al., 2012), a relevant feature after the results of the previous tests. Following this, we applied post-hoc tests to observe which pairs of subsamples were statistically similar or different, tests that tell us whether two or more subsamples more likely belong to the same distribution or population. For numerical variables, we used the post-hoc Dunn's test - a nonparametric multiple comparison of means suggested for unequal sample sizes (Pohlert, 2014; Zar, 2010) - and for categorical variables, the pairwise Chi-Squared test – a multiple comparison of proportions of subsamples. To account for the error of incorrectly rejecting the null hypotheses after multiple comparisons, we applied the p-value correction given by Holm (Field et al., 2012).

3.2.2.2 Multivariable regression (Stage 2)

With the aim of evaluating the contributions from each variable to the building loss ratio, we applied ordinary least squares (OLS) regression, given that different variable types were present and a comparatively large dataset was available (2283 observations for building loss ratio). With the latter, normality of the residuals could be overlooked (Hayes, 2018). The set of independent variables comprised individual variables (i.e. not composite variables), as it was easier to observe and understand the contributions from each predictor compared to composite variables (Hair et al., 2019). A final note is that isolating the causal effect of each variable is relatively unfeasible when studying retrospective loss data without complicated approaches (Hudson et al., 2014). Additionally, a simpler model is generally preferable to a complex one (McCullagh & Nelder, 1989). Therefore, we also applied a variable selection procedure to observe which variables were the best candidates to explain the monetary loss suffered.

Data preparation

In a regression framework, nonnormality and nonlinear relationships must be dealt with in order to increase the performance of the model. Hence, very skewed variables were log-transformed for the regression analyses, namely: duration, early warning lead time, gap between warning and action, house or flat area, building area, and building value. There were very few reported '0' values to generate significant sample selection issues.

The ordered variables, e.g. quality of warning or warning information, work on interval scales, with clear differences between responses. Therefore, we considered ordered variables as 'numeric' instead of nominal. Nominal variables without a natural ordering, e.g. building type, region, were converted into dummy variables.

Additionally, in order to further increase data comparability, we focus only on the data points which are most likely to have similar loss-generating processes. Therefore, we focus only on respondents whose loss ratio was in the interval (0, 1). The rationale for this is that observations outside of this range (zero or total loss) present extreme outcomes and therefore a different set of responses to the predictor variables is likely. These cases would require additional steps, e.g. including an additional probability model as in Rözer et al. (2019). We truncate the sample to include only the nonextreme cases as a methodological simplification for an otherwise minor but significantly different subsample. This truncation resulted in 2268 observations for the building loss ratio. The univariate analyses provided the initial input into this selection, which resulted in 'building value' being excluded from the analysis given that it is highly collinear with the building area.

Variable Selection

The iterative variable selection process was based on a stepwise variable selection from both random sampling (using 60% of observations available in each run, without repetitions) and bootstrapping (using 100% of the available dataset, with repetitions) (Hayes, 2018). We used both forward and backward elimination with resampling (James et al., 2013) in an iterative process in order to find a steady variable set. For each subsample, the process was repeated until the best performance was achieved through the Akaike Information Criterion - AIC (Vrieze, 2012). Albeit from different approaches, a relationship between the AIC and the p-value could be traced, and for this procedure we adopted the (rough) equivalent to a p-value of 0.05 as a threshold (Murtaugh (2014); see Stack Exchange (2014) for the code equivalent).

We employed an iterative approach because from our practical understanding and results from Wagenaar et al. (2018), data-driven models present significant differences in the final variable selection outcomes when trained with different subsamples. This is because different starting points and variable combinations can change the order in which variables are added or eliminated. For instance, because the test for data missing 'completely at random' was inconclusive, and because the fewer variables that are considered the larger the number of complete cases is, an iterative approach based on resampling/bootstrapping was used in order to account for this possibility.

Our iterative process was based on 1000 resampling runs per cycle. In the first cycle, all variables were included. Then, in each of the 1000 resamples, variables were eliminated based on the stepwise elimination process employed (based on achieving the best AIC). In each of the 1000 runs, the final set of selected variables was recorded. Then, the least selected variable was excluded from the analysis, after which a new cycle of 1000 runs was conducted with the remaining variables. The process was repeated until all predictors were selected at least 400 times (i.e. 40% of samples) in the same 1000-run cycle. The threshold of 40% was selected after preliminary rounds showed inconsistency among selected variables at lower rates. This approach was adopted because of the higher statistical capability of a larger dataset, and the variable selection focused the analysis on fewer variables and hence fewer potentially missing variables per observation.

Hair et al. (2019) emphasize that in stepwise procedures a ratio of at least 50:1 sample size to independent variables should be retained, since such procedures will select the "strongest relationships" and a small sample size risks losing the ability to generalize.

3.3 Results and Discussions

3.3.1 Univariate Assessments

3.3.1.1 Similarity of Flood Types' Subsamples

This section presents the results of the initial exploratory analysis of correlations and comparisons. Hence, we present central values (average or mode) of each variable and the pairwise comparison of the four subsamples of households affected by each flood type, after post-hoc tests in Table 3.3. We employed the multiple comparison error correction given by Holm and considered a p-value smaller than 0.05 as statistically significant. Notations 'a' to 'd' next to the central values denote subsamples that are statistically homogeneous, or at least not statistically different, for each given variable. Values with the same letter are thus deemed to be similar, but do not indicate magnitude order. For water depth, for example, riverine and surface water floods are similar to each other; therefore, both types belong to group 'b.' Both are, however, not similar to the levee breach – group 'a,' which is also dissimilar to groundwater floods – group 'c.' Two letters next to a central value means that the subsample is similar to both groups: for example, the warning quality for riverine floods is similar to that for both surface and groundwater floods, but different from levee breach cases. The complete pairwise comparisons are available in the Appendix A. Along Table 3.3, last column, we also see the number of different groups. A value of 1 implies that all subsamples are considered as homogeneous and hence as a single group, and a value of 2 or 3 indicates that there are 2 or 3 separate groupings, respectively, while a value of 4 indicates that all subsamples are heterogeneous.

Among the hazard variables, we see that those affected by a levee breach reported on average larger values for water depth, flood duration, and contaminated flood waters. Those affected by a surface water flood witnessed a higher water velocity and shorter duration, while those affected by rising groundwater saw the lowest values of water depth, velocity, and contamination though a mid-level duration.

In the variables regarding warnings, there is an overall difference between levee breaches and the other flood types. Moreover, similarities are also noticeable between riverine and groundwater floods regarding the warning lead time, the quality of the warning, and the gap between the warning and the start of emergency actions. In contrast, the warning information score and warning source were deemed different across all four flood types. There is also a similarity in the quality of the warning and the gap between warning and action between riverine and surface water floods.

The variables related to preparedness show mixed differences across groups. For both variables, the emergency measures score and the awareness of living in a flood-prone area, there are two similar groups: levee breaches and riverine floods, on the one hand, and

Table 3.3: Central Values of Each Variable per Flood Type Grouped by Similarity After Post Hoc Tests With a Significance of 0.05 (Central Value Is the Average of Numeric Variables, the Mode of Nominal Variables)

Variable	Unit or range	Levee breach (n=810)		Riverine (n=2509)		Surface water (n=447)		Ground-water (n=652)		Number of different groups
Hazard characteristics										
Water Depth	[cm]	107	a	51	b	58	b	-66	c	3
Duration	[h]	283	a	122	b	64	c	146	b	3
Velocity	[0-6]	2.9	a	2.9	a	3.6	c	2.2	b	3
Contamination	[0-2]	0.81	a	0.49	b	0.59	d	0.24	c	4
Warning										
Warning Lead Time	[h]	42	a	22	b	9	c	25	b	3
Quality of Warning	[1-6]	3.53	a	2.82	b,c	3.21	c	2.59	b	3
Warning Information	[0-16]	3.42	a	2.64	b	1.31	d	2	c	4
Warning Source	5 classes[1,5]	Off+Ev (38%)	a	Off (29%)	b	No (37%)	d	Off (29%)	c	4
Gap Warning-Action	[h]	18	a	5.4	b	3.74	b	8.11	a,b	2
Preparedness										
Emergency measures	[0-17]	5.35	a	5.64	a	4.61	b	4.85	a,b	2
Precautionary measures	[0-2]	0.59	a	0.78	b	0.58	a	0.68	a	2
Perceived efficiency of precautionary measures	[1-6]	3.16	a	2.77	b	2.63	b	2.65	b	2
Flood Experience	[0-4]	0.55	a	1.11	b	0.77	c	0.86	c	3
Awareness of Flood Risk	% of y	70%	a	72%	a	58%	b	64%	b	2
Insurance cover	% of y	50%	a	47%	a	40%	b	40%	b	2
Building characteristics										
Ownership	3 classes[1,2]	bO (83%)	a	bO (70%)	b	bO (74%)	b	bO (69%)	b	2
Build. Type	3 classes[1,3]	EFH (62%)	a	EFH (48%)	b	EFH (45%)	b	EFH (49%)	b	2
N of Flats	[1-40]	1.7	a	2.54	b	2.27	b	2.59	b	2
Build. Quality	[1-6]	2.19	a	2.3	b	2.24	a,b	2.41	c	3
Build. Value	[1000 €]	489	a	592	b	548	b	565	b	2
House/Flat area	[m²]	125	a	113	b	115	a,b	117	b	2

Central Values of Each Variable per Flood Type Grouped by Similarity After Post Hoc Tests (continued)

Variable	Unit or range	Levee breach (n=810)		Riverine (n=2509)		Surface water (n=447)		Ground-water (n=652)		Number of different groups
Building area	[m²]	185	a	246	b	216	b	268	b	2
Cellar	% of y	78%	a	82%	a	81%	a	93%	b	2
Household and socio-economic features										
Age	[y]	55.7	a	56.4	a	54	a,b	53.1	b	2
Household size	[n]	2.67		2.63		2.72		2.74		1
Children	[n]	0.24	a	0.3	a	0.34	a,b	0.4	b	2
Elderly	[n]	0.54		0.51		0.52		0.43		1
Income Class	[11-16]	14		14.1		14		14.2		1
Socio-Economic Status	[1-4]	2.94	a	2.72	b	2.73	b	2.63	b	2
Others										
Region	3 classes[1,4]	East (78%)	a	East (68%)	b	East (53%)	d	East (63%)	c	3
Event year	6 years	2013 (49%)	a	2013 (38%)	b	2002 (58%)	d	2002 (50%)	c	3
Monetary loss										
Building loss ratio	[%]	18	a	9	b	10	b	3	c	3
Building loss (2013 values)	[1000 €]	76	a	44	b	47	b	19	c	3

[1] For nominal variables, only the share of the most frequent class (mode) is shown

[2] bO: building owner

[3] EFH: detached houses

[4] see description of federal states' grouping at Table 3.2

[5] Off: official warning; +Ev: official warning with evacuation order; No: no warning

[a, b, c, d] notation of subsamples that are statistically similar to each other; same letters mean similar subsamples; two letters next to a central value means it is similar to both letters' groups (see text for reading example)

surface water floods and groundwater floods, on the other hand. Those affected by riverine floods had more recent experiences and also implemented more precautionary measures. The difference in experiences with other flood types, however, did not translate into a statistical difference in terms of our indicator for implemented precautionary measures. There is a higher share of insured households among those affected by levee breaches or riverine floods compared to those affected by surface or groundwater floods. This is an important difference to consider, because property-level adaptation is known to be effective at limiting flood losses, while insurance coverage alone is not (e.g. Hudson et al., 2014; Poussin et al., 2015).

Regarding the type of buildings affected by each flood type, there is a clear distinction between those affected by levee breaches and other flood types, the former featuring a higher proportion of detached houses and lower proportion of apartment buildings. This apparent relationship can be explained not as a causal relationship, but as an outcome of many of these levee-breaches occurring in rural areas where detached houses are dominant. Similarly, the number of flats, building value, building area, and flat area, follow the same pattern. On the other hand, building quality is higher on average, but not statistically different from those affected by surface water floods. More than 92% of those affected by groundwater have a cellar, in contrast to less than 82% among other flood types.

When comparing the information regarding the survey respondent and the respective household characteristics, one can see few differences across flood types. Information on building ownership is related to the building type as well. Therefore, a distinction is also observed: buildings affected by levee breaches, with a higher proportion of detached homes, also show a higher proportion of homeowners and lower proportion of tenants. Again, as the socioeconomic status according to Plapp (2003 apud Thieken et al., 2005) also includes ownership as one of its factors, the same pattern is noticeable. There is a statistically significant difference among the age of the respondents, with lower values for households affected by groundwater.

The final variables of interest are the monetary losses and loss ratio of the building. These variables display the same pattern, a significant similarity between those affected by riverine and surface water floods. Although comparing central values is a useful starting point, the extremes of the distribution must also be noted. For instance, groundwater floods reported a maximum loss ratio of 51% and a third quartile of only 3.6% (mean of 3.4%), while other flood types displayed a 100% loss ratio and median of 4% or more (mean of 9% or more). As noted in the a priori order of most damaging events by Hristova (2007), levee breaches are the most damaging events, groundwater floods are the least damaging, and riverine and surface floods are not significantly statistically different, not only in terms of losses but also in terms of variables from all other aspects as outlined above.

3.3.1.2 Discussion of the Univariate Analyses

From the univariate analyses we can notice some expected agreements; for instance, altogether, the data reflect what we would expect regarding flood types' hazard characteristics differences, while socio-economic features are mostly homogeneous. However, possible caveats to the results must also be observed. Here, only the most striking results are discussed: the links between warning and preparedness and risk mapping and forecast ability, and the presence of a cellar; a further discussion is provided later in combination with the regression analyses.

Some differences in warning and preparedness features reflect the ability to better forecast large advective events in comparison to convective rainfall events Einfalt et al. (2009) and Rözer et al. (2016). This is noticeable as a longer warning lead time, more warning information, and a higher share of people receiving an official warning among those affected by levee breaches, followed by those affected by riverine floods, and a worse outcome in this respect for those impacted by surface and groundwater floods. Moreover, the indicators for the number of emergency measures implemented, the awareness of living in a flood-prone area, and the share of insurance buyers are higher for levee breach- and riverine flood-affected households. We should note that many of these aspects overall have improved over time in Germany (see Kienzler et al., 2015; Thieken, Kienzler et al., 2016).

Differences in insurance penetration may be linked to risk perception and risk mapping, and also related to the expectation of governmental compensation (Seifert et al., 2013) or cultural factors that may vary in space and time. We should note that for riverine areas or areas (potentially) affected by levee breaches, the risk is better communicated, e.g. by hazard maps, or better perceived than for other flood types. In fact, the flood hazard zoning system (ZÜRS), published in 2001 by the German Insurance Association (GDV) and recently updated and made (partially) available to the public (Surminski & Thieken, 2017), accounts only for riverine floods. Surface and groundwater flood hazards are not mapped systematically, as these flood types occur in erratic places (Falconer et al., 2009; Parker & Priest, 2012). For comparison, a low average insurance penetration of approximately 20% have been found in households affected by pluvial floods in areas of Germany and the Netherlands (respectively by Rözer et al. (2016) and Spekkers et al. (2017)). Although in general we see in our dataset a larger insurance penetration for all flood types, and an expansion since 2002 (Thieken, Kienzler et al., 2016), the subsample of groundwater- and surface water-affected households still presents a significantly lower level. Additionally, insurance against groundwater floods is regularly not provided (Thieken et al., 2006), although compensation is possible in exceptional cases, i.e. if the loss by groundwater flooding is clearly linked to a preceding (river) flood event.

The higher presence of cellars in groundwater-affected households can be termed a ‘bias’ of exposure or a sign of an adaptation trend (from a lower presence of cellars in the subsamples of other flood types). Because there are no reliable census data available on the average of houses with cellars, we cannot infer more. The presence of a higher percentage of detached houses and owners in households affected by levee breaches might also be a ‘bias’ of exposure because these affected houses are generally located in the countryside, or at least far from city centers.

Finally, it is important to note again the exploratory nature of this section being unable to distinguish causal impacts or directions. For instance, the relationship between flood experience and flood type could be seen to be arbitrary and linked to the likelihood of flooding in the region. A similar argument could be made for building type, ownership or building quality and flood type, though the relationship with the cellar variable is more certain. Due to the nature of this section's analyses as a comparison of pairwise correlations, it is possible that some of these initial groupings across flood types may seem to be coincidences or a limited number of events. However, it is also important to keep in mind that, while not collinear, many of these variables are correlated within an event or area. This makes it a sensible starting point for detecting suspected groupings, which Stage 2 of the analysis (the regression framework) can refine when the influence of multiple variables regarding the loss ratio are jointly controlled for.

3.3.2 Regression Analyses (Stage 2)

In this section, we present the results of our variable selection procedure and the final set of predictor variables used in the following analyses, followed by the general and flood type-specific regression models. Later, we discuss both analyses.

3.3.2.1 Variable Selection

Table 3.4 shows the percentage of times that each variable was included in the last predictor set generated by each variable selection process. The resulting regression model includes all variables that were identified in at least two of the four processes employed. The different stepwise elimination processes generated different outcomes because the relationship among the (included) independent variables may be complex, masking or confounding their relationship to the dependent variable, affecting the result of the selection. Therefore, selecting variables that occur twice across elimination methods limits a potential bias from these complex relationships.

We see that in both types of procedures, seven variables were selected in more than 80% of the runs, i.e. water depth, building area, contamination, duration, precautionary measures, insurance coverage, and flood type (Table 3.4). As previous literature has indicated (Figueiredo et al., 2018; Kreibich & Thieken, 2008; Vogel et al., 2018) and our variable selection has reinforced, flood type is an important potential predictor from our dataset of different loss outcomes. Therefore, flood type seems to be a practical piece of information to collect.

It is sometimes suggested (Hair et al., 2019) that more rather than fewer variables should be retained in a regression when explanation is the aim rather than prediction. Therefore, we selected not only the most prominent variables in our selection process from Table 3.4, but also those identified to be more relevant in previous studies that used nonlinear and nonparametric methods over the same or similar dataset (Merz et al., 2013; Schröter et al., 2014; Vogel et al., 2018). From these studies, we singled out

Table 3.4: Percentage of variable inclusion in backward elimination and forward selection (at least 40% in 1000 runs), with building loss ratio as the dependent variable

#	Predictors	Backward Elimination		Forward Selection	
		Random sampling	Boot-strapping	Random sampling	Boot-strapping
1	Water Depth	100	100	100	100
2	Building area (Variable was log-transformed)	100	100	100	100
3	Contamination	100	100	100	100
4	Duration (Variable was log-transformed)	100	100	100	100
5	Precautionary measures	99	99	100	98
6	Insurance cover	66	88	79	88
7	Flood Type		83	85	83
8	Perceived efficiency of precautionary measures (Efficiency Pre.)	65	68	62	68
9	Emergency measures	58	66		65
10	Cellar	45	63		62
11	Velocity		60		60
12	Flood Experience	43	51		51

only those predictors that were selected more than once across their variable selection methods. Details on this selection procedure and the specific methods are available in the Appendix A and Table A.1). Nine variables were singled out in this procedure, seven of which agreed with the results of our variable selection process. The year of the event and the building quality were repeatedly included in the abovementioned literature as important variables. However, since the year of the event is less fit for transferability exercises, only the building quality was added to our 12 initially selected variables shown in Table 3.4.

In the first steps of the stepwise iteration process, we begin with 31 potential predictors and 316 complete data points. However, as variables are excluded the number of complete data points increases. In the final selected 13 predictor variable set, there are more than 1800 complete data points. Therefore, the initial stages may suffer from the problems identified by Hair et al. (2019), but become potentially less problematic as the sample size increases to over twice the ratio suggested by Hair et al. (2019). This does, however, create the potential limitation that the initial steps may be overly driven by sample-specific concerns.

3.3.2.2 Multiple Regression per Flood Type

With the now 13 selected variables, we fit a linear regression to the whole dataset (1812 complete-set data points) and separately for each flood type subsample. The

Table 3.5: Standardized coefficients and statistical significance of variables included in the linear regression of the complete set or per flood type

Variable	All	Levee breach (1)	Riverine (2)	Surface water (3)	Ground water (4)
n of complete data points	1812	368	976	217	251
Hazard characteristics					
Water Depth	0.0499 ***	0.0650 ***	0.0452 ***	0.0414 ***	0.0323 ***
Duration[1]	0.0165 ***	0.0123 .	0.0149 ***	0.0225 *	0.0071 .
Velocity	0.0060 *	0.0081	0.0048	0.0109	-0.0007
Contamination	0.0188 ***	0.0265 ***	0.0127 ***	0.0371 ***	0.0019
Preparedness					
Emergency measures	-0.0061 *	-0.0014	-0.0064 .	-0.0099	-0.0019
Precautionary measures	-0.0116 ***	0.0007	-0.0138 ***	-0.0164 .	-0.0130 **
Perceived efficiency of precautionary measures (efficiency Pre.)	0.0065 *	0.0121 .	0.0044	0.0095	0.0032
Flood Experience	-0.0052 .	-0.0222 **	-0.0044	0.0111	-0.0005
Insurance cover	0.0152 **	0.0372 **	0.0186 **	-0.0210	-0.0016
Building characteristics					
Building Area[1]	-0.0287 ***	-0.0376 ***	-0.0274 ***	-0.0231 **	-0.0151 ***
Building Quality	-0.0066 **	-0.0044	-0.0051	-0.0175 *	-0.0052
(No) Cellar	0.0152 *	0.0195	0.0096	0.0293	0.0171

[1] log-transformed variables for linear regression. ***P<0.001; **P<0.01; *P<0.05; . P<0.1

comparison among coefficients of different variables is more reasonable with standardized coefficients (Hair et al., 2019), where the distribution of data within the subsample is accounted for and the units are standardized (i.e. the unit is one standard deviation for continuous variables), as shown in Table 3.5 and Figure 3.2. The fitted unstandardized coefficients and statistical indicators are shown in Table A.2.

When separating the regression per flood type subsample, the variables' importance changes (extended tables for each regression are presented in Tables A.3 to A.7). However, it is still evident that the selected predictors are important either for overall loss modeling, across flood types, or at least for one flood type-specific model (Table 3.5). We highlight that flood experience was one of the least selected variables (see Table 3.4) and building quality was added later, but they were termed significant for levee breach- and surface water flood-specific models, respectively (Table 3.5).

As noticeable in Table 3.5, the subsamples for surface water or groundwater flooding are smaller in terms of observations, and therefore have lower statistical power. Therefore, their signal is generally less accurate, as visible in Figure 3.2. In Figure 3.2, we compare the relevance of each factor for the final loss ratio. The estimates beginning with "FT_" stand for the dummy variables created after each flood type for the overall model, where levee breach is the reference category (i.e. estimate equals 0, not shown).

With standardized variables (centered on the mean and with variation relative to the standard deviation), one can see that water depth is the most important factor overall,

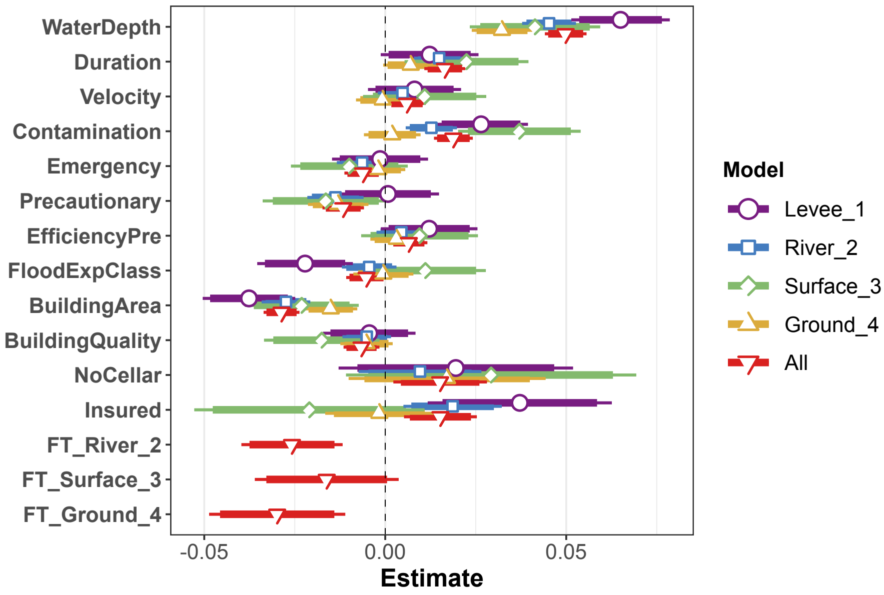

Figure 3.2: Standardized regression coefficients of the overall and flood type-specific models with 90% confidence interval thick bars. "FT_" stands for the dummy variables after flood types, where levee breach is the reference

as has been reflected in flood loss modeling since at least the 1970s (Grigg & Helweg, 1975). In the regression of the whole sample, there is no overlap between the two most important factors, water depth and building area, but there are overlaps between other factors. For levee breaches, both the building area and the state of being insured stand as the second most important factors, although the latter has quite a 'spread-out' estimate. This is followed by flood experience class and contamination (see Table 3.5, Fig. 3.2).

For riverine floods one can identify building area as the second most important factor, after water depth, followed by four factors – insurance, flood duration, precautionary measures, and contamination - with high statistical significance and estimates overlapping each other, making their order of importance less distinguishable.

Due to the smallest subsample, all coefficients for surface water floods are more 'spread-out' than for other flood types subsamples. This is due to the lower statistical power, and hence greater uncertainty. Therefore, we see that contamination is not only more important for surface water floods than for other flood types, but its importance is also quite similar to that of water depth. Following this, building area, duration, and building quality show a similar importance.

Finally, for rising groundwater, building area and precautionary measures are in the second order of importance, and duration is the last statistically significant factor though already of smaller importance.

3.3.2.3 Discussion of the Regression Analyses

In this section, we first compare our set of selected variables with other previous modeling efforts and discuss its possible caveats. Later, we discuss the differences among the flood type-specific regression models.

As hypothesized, flood type is a highly relevant predictor among the variables selected in more than 80% of random sampling runs for building loss ratio regressions (Table 3.4; see also Table 3.5, Fig. 3.2, and Table A.2). It is worth noting that besides hazard and building characteristics, features of preparedness were frequently selected, although these variables are rarely considered in flood loss models.

Variables related to flood warning were deemed of low relevance for the building loss ratio (Table 3.5), even though they were heterogeneous per flood type subsample (Table 3.3). This disagreement can be a result of mediated or interaction effects, i.e. a variable's effect on the loss is influenced by another variable. For example, as mentioned by Kreibich, Müller et al. (2017), the response is believed to be related to the warning lead time, by observing the responses from affected households and companies claiming that they would have acted (or done more) if they had been warned earlier. It should be acknowledged that flood warning has been considerably improved in Germany after 2002 (Kreibich, Müller et al., 2017; Thieken, Kienzler et al., 2016), and thus might lead to heterogeneous patterns in the data set. This issue of moderation or mediation effects could be dealt with e.g. through multilevel modeling. This advanced analysis, however, is outside the scope of this paper and shall be left to future research.

From the German survey data we used, distinct modeling approaches have been developed, all of them predictors related to preparedness. Of the models reviewed by Gerl et al. (2016), only eight models included at least one variable from household features or preparedness, three of which use the same survey data (or parts of it) used for this paper. It must also be noticed that, after the 2002 floods, early warning systems, levees, flood risk management, infrastructure, and communication improved in Germany, although not equally across the federal states (Kreibich, Müller et al., 2017; Thieken, Kienzler et al., 2016). Also, in the overall Bayesian Network (BN) developed by Vogel et al. (2018), the year of the event is closely linked to precaution, contamination, insurance, etc., since these items have changed significantly in recent years. Such evolution is pointed to as one of the main reasons why the 2013 flood was not as damaging as the flood of 2002 (Thieken, Kienzler et al., 2016), which reinforces that flood loss models should include preparedness as explaining variables.

Since 2005, the Federal Water Act of Germany includes a paragraph stating that every person should take mitigating actions according to their own capacity (Thieken, Bessel et al., 2016). Additionally, the Federal State of Bavaria recommends monitoring and maintenance of the fail-safe measures of oil tanks (LfU, 2014 apud Thieken, Bessel et al. (2016)), as this is an important source of contamination in floods which can also increase loss (Kreibich et al., 2011). Such actions show an escalating but still incomplete improvement of flood management in Germany, which reinforces the need to monitor such actions and consider them in flood loss estimations.

The most relevant study to compare ours to is the Markov-Blankets (MB) approach from (Vogel et al., 2018), in which the authors compared different flood types. In general, our procedure signaled more variables as being relevant for loss-ratio modeling than in the respective MBs (see Table 3.6). Our results, however, display a degree of similarity with those from Vogel et al. (2018), except for the variables that were not considered in the study and one case, the presence of duration, which appears as an important predictor for levee breach-MBs - but only of marginal significance in our linear regression selection. Comparing our work to that of Vogel et al. (2018), we reinforced in the previous section the potential order of importance of the influencing factors. In Table 3.6 we compared the more important variables of our selection procedure and the ones included in the Markov-Blanket from Vogel et al. (2018). The statistically significant predictors of our regressions are numbered according to the order of the coefficient estimates of the absolute mean, although their confidence intervals may overlap, as discussed above and shown in Figure 3.2. The ordering of variables is not possible using MBs.

It could be argued that the year of the event is not a helpful predictor of model transferability in a single-level regression framework, but only as a nominal variable to help explain differences among the included events that the selected variables were not able to explain. Even though not selected for our potential predictor set, we compared our results with a model including the year of the event as dummy variable, but in fact it was not considered as significant in our regression framework (see Table A.2).

Although causality cannot be tested, below we present interpretations of the reasons for differences in the significance and coefficients of predictor variables across flood type-specific models. Regarding flood experience, it is only significant for levee breach cases. This flood type being posed as the most destructive one (highest water depth, duration, and level of contamination, see Table 3.3), it may be argued that it requires a high level of preparedness for it to be effective, and, as found in Lechowska (2018), a personal experience with flood influences awareness and preparedness more effectively than acquiring information from third parties (media or acquaintances). However, both emergency measures and precautionary measures were not deemed as significant for the levee breach-specific model, but the grading of the perceived efficiency of precautionary measures is slightly more significant than it is for other flood types. This indicates that there might be a confounding factor or a missing variable that explains this complexity.

Table 3.6: Comparison of relevant variables from linear regression of Markov-Blankets developed per flood type

	Linear regression (significant coefficients)[b]					Markov-Blanket (Vogel et al. 2018) [c]				
	All	Levee breach	Riverine	Surface water	Groundwater	All	Levee breach	Riverine	Surface water	Groundwater
Water Depth	1	1	1	1	1	X	X	X	X	X
Building area[a]	2	2	2	3	2	X		X		
Contamination	4	4	6	2		X				
Precautionary measures	8		5	6	3					X
Duration	5	6	4	4	4	X	X			
Insurance cover	6	3	3							
Flood Experience	13	5					X			
Building Quality	9			5						
Efficiency Pre.	10	7								
Emergency measures	11		7							
Velocity	12									
Cellar	7							Not considered		
Event year			Not selected			X		X		
Building Type			Not selected				X			
Income class			Not selected						X	
Flood Type	3					X				

[a] Considered as building value in the work of Vogel et al. which was posed as collinear with building area, as explained in section 3.2
[b] The numbers show the order of the absolute mean of the coefficient estimate for a given linear regression
[c] "X" denotes inclusion of a variable in a given Markov-Blanket

The estimates for flood experience are mainly negative, meaning that more recent experience leads to lower losses, which is in line with the strong connection between flood experience and preparedness or precaution (Bubeck et al., 2012; Lechowska, 2018; Osberghaus, 2017). This could be due to the cross-over with memory effects and the forces behind adaptation. Yet, the estimate for surface water floods is positive. We see, however, that the signal is very uncertain and its statistical significance is low, so that we conclude that its meaning is not strongly relevant.

A similar case of an uncertain signal occurs with the estimate for insured households. For households affected by levee breaches or riverine floods, the signal is positive, while for groundwater the signal is around zero. However, with surface water flooding the signal has a negative mean but ranges widely. Such contrasting signals are in agreement with the literature, since there is evidence of both: insurance leading to maladaptation or encouraging risk reduction (Surminski & Thieken, 2017).

Building quality is only statistically relevant to the surface water flood subsample. We argue that in the shortest, fastest floods (surface floods) building quality may resist some loss, while in longer flooding events water will eventually take its course anyway. It could be supposed that higher building quality is better able to withstand the hydraulic forces of surface water floods, because in other flood types penetration is the dominating process, while flash floods can cause structural damage to buildings. It is important to note that we grouped together flash floods and pluvial (urban, heavy rain) floods, despite some development differences, since their distinction is not always clear and, even summed up, they still comprise the smallest group. Due to possible differences in flood dynamics (e.g. velocities) and resulting losses, a distinction between flash floods and pluvial floods would be worthwhile to consider if the database allows us to distinguish between the processes. We acknowledge that more dynamic floods characterized by fast onset with a high load of sediments or wave activity, such as in torrent processes (Fuchs, Heiser et al., 2019) and coastal floods (Penning-Rowsell et al., 2013), were not addressed here, but rather flood types more frequently present in medium- and lowlands in Germany, from which we could gather a uniform, broad dataset. This dataset addresses several aspects of the damaging process, not only the hazard itself but also indicators of vulnerability and socio-economic aspects, a development that has also been challenging in other regions and hazard types (Fuchs, Heiser et al., 2019).

Performance in modeling was not the focus of this work, but rather explanation. Yet, a small improvement can be observed, with the Root Mean Squared Error (and Median Absolute Error) reducing from 10.6% (5.0%) to 10.4% (4.6%) when comparing predictions using one overall model or the four flood type-specific models.

3.4 Conclusions

In this study, we sought out the differences in the potential predictors of monetary flood loss to residential buildings across different flood types in Germany. From a broad dataset of German households affected by floods across six different events, we conducted univariate and regression analyses that sought to indicate which variables acted as better predictors of the building flood loss ratio for affected households in general and how the relevance of these predictors differ across separate flood types.

After conducting a variable selection process to reduce the initial set of predictor variables for the loss ratio, and a qualitative check with the wider literature, we find 13 significant variables stretching across the hazard, preparedness, and building characteristics domains. Each of these 13 variables was found to be a significant predictor of the building loss ratio in at least one flood type-specific model or in the overall model. So far, most loss models have focused on riverine floods and have tended to use the same narrow set of predictor variables. However, our findings indicate that this might not always be suitable for loss modeling across different flood types. Some variables that are usually not considered for riverine floods are more relevant for other flood types: For example, contamination shows itself to be very relevant for surface water, but less so for riverine floods, and is of less or no importance for groundwater floods. Previous flood experience gives a clearer signal, in a predictive sense, for lower losses in households affected by levee breaches than for any other flood type. Finally, the building quality, a predictor deemed important for surface water floods only, could show a distinction in structural damage resistance. As we noted before, all the six reported flood events can be termed as compound flood events. In such a situation, the abovementioned specificities must be incorporated in the loss modeling. There is room for improvement in the loss models to differentiate between the weights of factors across different flood types. This is due to how the losses of different flood types are driven by different processes even though water depth remains an important variable. Therefore, there is an opportunity for future work to expand upon this in several directions. The first is testing the applicability of broadening the range of data used in flood loss modeling training and development. A second avenue could be the development, and later synthesis, through Bayesian techniques, of differently focused flood loss models.

While improved data collection for flood loss modeling or post-event forensic analysis is a highly demanded task, it is a very resource-intensive one. Our findings indicate which information could be prioritized when collecting data to understand the impacts of a given flood type, which should help to steer data collection efforts toward reducing costs and fostering loss modeling. One example is that data gathering efforts should be broadened to systematically include emergency and precautionary measures. For instance, as can be seen in Table 3.6, we find that precautionary measures were important in four of the five model sets (as compared to one in Vogel et al., 2018). Emergency behavior was also found to be important but to a lesser extent, highlighting the need to prepare for a flood over the longer term. Moreover, Figure 3.2 highlights how the impacts associated with these variables can differ significantly across flood types. Therefore, when combined with the wider literature investigating the effectiveness of precautionary behavior, we see that these variables should be included more often in loss modelling and risk analyses, as the actions of those at risk can change the effective level of risk faced and the resulting accuracy of risk assessments informed by risk models. Still in this domain, notwithstanding how the levels and features of early warning systems differ among the flood types, they were not included in the estimation model. This could be due to indirect influence that is not easily implemented in a single-level linear regression, indicating that further work should explore interactions between features/predictors. Moreover, it is possible that other predictors interact the same way that multicollinearity has been observed in at least one pair of variables (building value vs. building size), which may mask relevant effects in the loss ratio. This refinement must be further analyzed with different modeling and statistical methods.

A linear regression, without considering the overwhelming possibilities of interactions across the predictor variables, should, therefore, capture only the dominant effects on loss. Moreover, splitting the database into each event or each federal state to account for space and time variability would lead to very small subsamples, decreasing the statistical power or even making the above-presented analyses unfeasible. Possible trends in time and space, not thoroughly explored in this work because the year of the event and the region/state of the household as predictors were not termed significant within our approach, are therefore subject to further research. Nonetheless, we contribute to the evidence supporting the assertion that information addressing preparedness is highly relevant for loss modeling; at the same time, we reduced the number of variables to be focused on, another step towards improving estimates, data collection, and supporting flood risk reduction.

By providing the order of importance of predictor variables, one can prioritize data gathering and, in the case of a more essential variable that is not directly available, decide to find a proxy, for instance, through hydraulic modeling for hazard characteristics or a census for regional or district socio-economic characteristics, or turn to new modeling developments that address preparedness behavior. While the primary purpose of the paper was to gain insights into the relevant variables per flood type regarding loss modelling, our findings indicate that there could be substantial differences in the loss-generating process across flood types. Our evaluation of the predictor variables' order of importance highlights these differences beyond only noticing common important drivers. However, this has implications for loss modelling more generally. This is because in each of the six floods studied, multiple different flood types were observed during the event, although all of them were considered as riverine as a whole. Therefore, loss assessments that assumed a pre-dominate flood type will require more nuanced methods. A nesting of regression models, say through multi-level models, may be a suitable way forward in future research given the limitations highlighted.

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Chapter 4

Residential flood loss estimated from Bayesian multilevel models [1]

Abstract Models for the predictions of monetary losses from floods mainly blend data deemed to represent a single flood type and region. Moreover, these approaches largely ignore indicators of preparedness and how predictors may vary between regions and events, challenging the transferability of flood loss models. We use a flood loss database of 1812 German flood-affected households to explore how Bayesian multilevel models can estimate normalised flood damage stratified by event, region, or flood process type. Multilevel models acknowledge natural groups in the data and allow each group to learn from others. We obtain posterior estimates that differ between flood types, with credibly varying influences of water depth, contamination, duration, implementation of property-level precautionary measures, insurance, and previous flood experience; these influences overlap across most events or regions, however. We infer that the underlying damaging processes of distinct flood types deserve further attention. Each reported flood loss and affected region involved mixed flood types, likely explaining the uncertainty in the coefficients. Our results emphasise the need to consider flood types as an important step towards applying flood loss models elsewhere. We argue that failing to do so may unduly generalize the model and systematically bias loss estimations from empirical data.

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4.1 Introduction

The estimation of flood losses is a key requirement for assessing flood risk and for the evaluation of mitigation strategies like the design of relief funds, structural protection, or insurance design. Yet loss estimation remains challenging, even for direct losses that can be more easily determined than indirect losses (Amadio et al., 2019; Figueiredo et al., 2018; Meyer et al., 2013; Vogel et al., 2018). Numerous methods of inferring flood damage from field or survey data have been tested, if not validated, with varying degrees of success (Gerl et al., 2016; Molinari et al., 2020).

Without standard loss documentation procedures in place, the highly variable losses caused by different flood types (e.g. pluvial, fluvial, coastal) can make loss modelling particularly challenging, especially where data are limited or heterogeneous. This lack of detailed or structured data motivates most modelling studies concerned with flood loss to assign just a single type of flooding to each event (Gerl et al., 2016). Another confounding issue is scale: inventories of flood damage are often aggregated at administrative levels such as municipalities or states (Bernet et al., 2017; Gradeci et al., 2019; Spekkers et al., 2014). This aggregation masks links between damage and exposure or vulnerability at the property scale (Meyer et al., 2013; Thieken, Bessel et al., 2016). These unstructured or aggregated data make damage models prone to underfitting, whilst training models with numerous predictors may lead to overfitting, reducing the ability to generalise and transfer to situations where information is unavailable (Gelman et al., 2014; Gerl et al., 2016; Meyer et al., 2013). Previous work has emphasised this challenge of transferring models with respect to different flood types, events, or locations (Cammerer et al., 2013; Figueiredo et al., 2018; Jongman et al., 2012; Schröter et al., 2014).

In this context, multilevel or hierarchic models are one alternative and offer a compromise between a single pooled model fitted to all data and many different models fitted to subsets of the data sharing a particular attribute or group. Bayesian multilevel models use conditional probability as a basis for learning the model parameters from a weighted compromise between the likelihood of the data being generated by the model and some prior knowledge of the model parameters. These models explicitly account for uncertainty in data, low or imbalanced sample size, and variability of model parameters across different groups (Gelman et al., 2014; McElreath, 2016). There are several approaches to the bias-variance trade-off (McElreath, 2020). We conduct a variable selection through cross-validation to achieve a balance between predictive accuracy and generalization. Using priors in the Bayesian framework is using regularization by design and keeps the model from overfitting the data (McElreath, 2020).

In contrast to empirical models, synthetic models are developed based on expert opinion and offer a good approach to harmonize loss estimations. However, how these models rely on assumptions is problematic when preparedness and other behavioural variables are concerned. In general, synthetic models tend to reduce the variability of data and remain rarely validated (Sairam et al., 2020). Therefore, we train our Bayesian model using reported data.

In this study, we use survey data from households affected by large floods throughout Germany between 2002 and 2013 (Thieken et al., 2017). These data go beyond addressing physical inundation characteristics by offering a broad view of the damaging process including the flood types that affected the households (i.e., floods from levee breaches, riverine floods, surface water floods, or rising groundwater floods).

Mohor et al. (2020) used this database to explore the most relevant factors for estimating relative loss of residential buildings with a regression model. From a larger pool of candidate variables, the authors selected 13 predictors of the flood hazard, building characteristics, and preparedness, including flood type as an indicator, and suggested that the influencing factors contribute with different magnitudes across flood types. Vogel et al. (2018) trained Bayesian Networks and Markov Blankets (MBs) for different flood events and types in Germany, obtaining varying compositions of meaningful predictors. Bayesian Networks focus on the dependence between variables and flow of information (Vogel et al., 2018), rather than the weight of each factor into the final loss, which is the case of Bayesian Inference.

Here we expand on the model of Mohor et al. (2020) by acknowledging structure in the dataset and explore whether a single regression model can apply not only to different flood types, but also to regions or flooding events. Single flood events can affect cities differently across regions, likely reflecting socioeconomic and geographic conditions and building codes, for example. These characteristics reflect a given asset's resistance to the hazard process (Thieken et al., 2005). These characteristics may differ on the level of administrative regions, and hence we considered a multi-level model variant structured by regions. Additionally, flood preparedness evolved over time, documented, for example, by Kienzler et al. (2015) and Thieken, Bessel et al. (2016) for Germany. Economic situations may also change the relative value of exposed assets and its recover or repair costs (Kron, 2005; Penning-Rowsell, 2005). Such changes are challenging to include in loss models, however. Therefore, we considered a third model variant structured by flood events, capturing the timely aspect. Therefore, estimate relative flood losses in Germany with a Bayesian multilevel model featuring three different groups, i.e. (i) flood types, (ii) administrative regions, and (iii) individual flood events to learn which predictors might aid the transferability of loss models. We hypothesise that the effect of some predictors varies with flood type, administrative region, or flood event. We use multilevel linear regression to explore these possible differences. Judging from previous work, we expect differing socioeconomic conditions or preparedness across regions of Germany (Kienzler et al., 2015; Thieken et al., 2007), a gradual development of building standards and preparedness (Kienzler et al., 2015; Vogel et al., 2018), and differing hazard characteristics and resistance across flood types (Mohor et al., 2020).

4.2 Data and Methods

4.2.1 Data

In this study we use the data from a joint effort that conducted surveys among households affected by large floods throughout Germany to investigate various aspects of the flood damaging process more systematically. Beginning with the large central-European floods of 2002, this database has more than 4000 entries from six different flood events (Thieken et al., 2017). The surveys had approximately 180 questions, with slight adaptations and improvements in clarity in each edition, and were conducted after major floods that hit Germany in 2002, 2005, 2006, 2010, 2011, and 2013. These floods happened in different seasons and involved different weather conditions that led to varying flood dynamics, i.e. riverine floods, surface water floods, rising groundwater floods, and levee breaches (Kienzler et al., 2015; Thieken, Bessel et al., 2016). While the floods in 2002, 2005, and 2010 evolved quickly, the floods in 2006, 2011 and 2013 were slow-onset events. In all cases, the eastern and the southern parts of Germany were affected the most.

These data go beyond addressing physical inundation characteristics, and also include aspects of warning, preparedness and precaution at the level of individual households. This gathering of socioeconomic information and building characteristics thus offers a broad view of the damaging process rarely found elsewhere (Thieken et al., 2017). This dataset also specifies the flood types that affected the households in four categories: floods from levee breaches, riverine floods, surface water floods, or rising groundwater floods. Multiple flood types were reported for the same event, even within the same city, thus giving rise to compound events that can be defined as the synchronous or sequential occurrence of multiple hazards (Zscheischler et al., 2020).

From this dataset, Mohor et al. (2020) identified thirteen predictors via variable selection in a multiple linear regression framework. Flood type was considered as a categorical or indicator variable (Gelman & Hill, 2007). These selected predictors are ranked in order of importance, according to the number of times the predictor was kept in an iterative variable selection procedure with random sampling (Table 4.1). A more detailed description of the variables and the method can be found in Vogel et al. (2018) and Mohor et al. (2020).

Table 4.1: Description of potential predictors of flood loss

	Predictor	abbr.	Unit /description
1	Water depth	WD	in cm
2	Building area	BA	originally in m^2; due to high skewness, the variable is log-transformed
3	Contamination	Con	indicator from 0 (none) to 2 (heavy contamination)
4	Duration	Dur	originally in h; due to high skewness, the variable is log-transformed
5	Property-level Precautionary Measures (PLPMs)	Pre	indicator from 0 (none) to 2 (very good precaution)
6	Insured	Ins	yes/no
7	Perceived efficacy of PLPMs	Eff	Likert-type scale from 1 (highly effective) to 6 (highly ineffective)
8	Emergency measures	Eme	indicator from 0 (no emergency measures performed) to 17 (many emergency measures performed effectively; Thieken et al., 2005)
9	Cellar	Cel	yes/no
10	Relative flow velocity	Vel	Likert-type scale from 0 (no flow) to 6 (very high velocity)
11	Flood experience	Exp	5 classes from 0 (no previous flooding) to 4 (more often and recent previous flooding)
12	Building quality	BQ	Likert-type scale from 1 (very high quality) to 6 (very low quality)

In this study, we used three characteristics to group our data: (i) flood type, with categories levee breaches, riverine, surface, and groundwater floods; (ii) regions of Germany, with categories south (Bavaria and Baden-Wurttemberg), east (Brandenburg, Mecklenburg-Western Pomerania, Saxony, Saxony-Anhalt, and Thuringia); as well as west and north (Hesse, Lower Saxony, North Rhine-Westphalia, Rhineland Palatinate, and Schleswig-Holstein - grouped together due to the low number of cases); and (iii) flood year, i.e. 2002, 2005, 2006, 2010, 2011, and 2013. We tested three model variants, each using only one group variable at a time (Table 4.2). We refer to these model variants as the flood-type model, the regional model, and the event model, respectively.

4.2.2 Methods

Single-level multiple linear regression is adequate for capturing general trends in data, but ignores structure in the data, such as flood type or region affected. We explore the suitability of a Bayesian multilevel model to estimate relative building loss (or loss ratio) from models with different predictor combinations. We use a numerical sampling scheme for Bayesian analysis implemented in the `brms` package (version 2.11.1; Bürkner, 2018)

Table 4.2: Number of instances in the training set used across grouping variables flood type, region, and event year (n = 1269)

Flood Types	Levee Breach	Riverine	Surface	Groundwater	Sum (n)
Flood events					
2002	110	252	103	106	571
2005	8	35	7	6	56
2006	0	25	2	3	30
2010	31	86	19	5	141
2011	1	49	5	11	66
2013	108	236	16	45	405
Regions of Germany					
South	52	174	53	58	337
East	205	469	80	111	865
West and North (W+N)	1	40	19	7	67
Sum (n)	258	683	152	176	1269

in the `R` programming environment (version 4.0.1; R Core Team, 2020). We test and compare various multilevel models with differing complexity. We trained the model on 70% of the complete dataset (no missing data), with a total of 1269 data points in the training dataset and 543 data points in the testing dataset. Although the dataset consists of more than 4000 datapoints, due to random missing data, the testing and training subsets size depends on the variables included in the model. Thus, 1812 datapoints were available in our case.

4.2.2.1 Bayesian multilevel model

Bayesian multilevel models weigh the likelihood of observing the given data under the specified model parameters by prior knowledge. Bayesian models thus express the uncertainty in both the prior parameter knowledge and the posterior parameter estimates. The multilevel approach allows us to analyse all data in one model while honouring structure or nominal groups in the data. Thus, the training of the group-specific parameters occurs at the same time so that model parameters can inform each other by means of specified (hyper-)prior distributions. This approach warrants more training data than running stand-alone models on subsets of our data, which in turn are more prone to over- and underfitting and overestimates of the regression coefficients, while reducing effects of collinearity, and offering a natural form of penalised regression (McElreath, 2016). The (unnormalized) posterior density, i.e. the probability distribution of the model parameter(s) θ given the observed data y of a Bayesian model is proportional to the product of the prior of the model parameters—a probability distribution describing previous knowledge about the model parameters—and the plausibility of observing the data given the model under these parameter choices, also known as likelihood (Gelman et al., 2014). The unnormalized posterior density can be written as:

$$p(\theta|y) \propto p(\theta)p(y|\theta) \tag{4.1}$$

In a multilevel model, the data are structured into J groups, with model parameters allowed to vary between these groups (θ_j). The vector of group-level parameters θ_j is itself drawn from a distribution specified by hyperparameter(s) τ. The model returns parameter estimates for both the entire (pooled) data and its J groups, although all parameters are learned jointly via the specified distribution of the hyperparameters. The group-level (hyper-)parameters are unknown and learned from the data to inform the posterior distribution. This relationship can be written as the joint prior distribution (Gelman et al., 2014):

$$p(\theta, \tau) \propto p(\tau)p(\theta|\tau) \tag{4.2}$$

The joint posterior distribution can then be written as (Gelman et al., 2014):

$$p(\theta, \tau|y) \propto p(\theta, \tau)p(y|\theta) \tag{4.3}$$

The `brms` package is an interface for building multilevel models (Bürkner, 2018) that uses STAN, a programming language for Bayesian statistical inference (Carpenter et al., 2017). STAN uses a Hamiltonian Monte Carlo (HMC) method, a type of random sampling to approximate posterior distributions that are without analytical solutions (Kruschke, 2014), or the extension of HMC, the No-U-Turn Sampler (NUTS), which is the default option in `brms` (Bürkner, 2018).

The choice of the likelihood and the priors should follow assumptions about the data-generation process (Gabry et al., 2019). Our response variable is relative loss, and relates total direct, tangible flood loss such as repair and replacement costs (Merz et al., 2010) to the total asset value of a given residential building; relative loss thus varies from 0 to 1. Recent work on flood loss modelling used an inflated beta distribution to first model the probability of no loss (Rözer et al., 2019), or of total loss using a zero-and-one inflated beta distribution (Fuchs, Heiser et al., 2019); a beta distribution then serves to estimate intermediate losses (Evans et al., 2000). This approach is useful in cases where flood damages remain unreported or unaccounted for. Our dataset of affected households has only 15 instances where relative flood loss was either 0 or 1. Hence, we dismissed those instances and modelled only partial loss ratios using the beta distribution:

$$y \sim \text{Beta}\left(\mu\phi, (1-\mu)\,\phi\right) \tag{4.4}$$

Where y is the loss ratio that we assume follows a beta distribution with parameters mean μ and precision ϕ. The mean (μ) is estimated from a multiple linear regression with K predictors as:

$$\text{logit}(\mu_i) = \alpha_0 + \alpha_{j[i]} + \mathbf{X}_{i,k}\boldsymbol{\beta}_{k,j[i]} \tag{4.5}$$

Where subscript i refers to each datapoint, subscript k refers to the predictors; subscript j refers to the groups; α_0 is the population-level intercept, $\boldsymbol{\alpha}_j$ is the vector of group-level intercepts; $\mathbf{X}_{i,k}$ is the $i \times k$ matrix of predictor values; and $\boldsymbol{\beta}_{k,j}$ is the $k \times j$ coefficient matrix. Each data point i is thus a vector of group-level coefficients, expressed by the $j[i]th$-column of $\boldsymbol{\beta}$. The model therefore has one population-level parameter (α_0) and $(k+1) * j$ group-level parameters ($\boldsymbol{\alpha}_j$ and $\boldsymbol{\beta}_{k,j}$).

In `brms`, the multilevel structure of the regression specifies Gaussian prior distributions for the intercepts $\boldsymbol{\alpha}_j$ and for the predictor coefficients $\boldsymbol{\beta}_j$ with fixed zero means and unknown standard deviations. The group-level standard deviations are hyperparameters that are common to all group levels, but individual for the intercept or for each given predictor (σ_α and $\boldsymbol{\sigma}_{\beta_k}$). Therefore, we use standardised input data that are centred at zero and scaled to unit standard deviation. The prior of each group-level standard deviation is in turn a weakly informative Gamma distribution with shape and inverse scale (or rate) parameters (2, 5), which accumulates most probability mass at low positive values below 1. This choice of prior is appropriate for standardised input data even without any specific prior knowledge, for example, from other studies on flood damage. While previous studies have indicated consistently that the effect of water depth is positive, we decided to keep the priors weak enough to allow for the possibility of either positive or negative estimates for all predictor coefficients to explore possible effects of the multi-level model. The prior for ϕ is non-informative.

$$\alpha_j \sim \mathcal{N}(0, \sigma_\alpha) \tag{4.6}$$

$$\sigma_\alpha \sim \text{Gamma}(2, 5) \tag{4.7}$$

$$\beta_{k,j} \sim \mathcal{N}(0, \sigma_{\beta_k}) \tag{4.8}$$

$$\sigma_{\beta_k} \sim \text{Gamma}(2, 5) \tag{4.9}$$

$$\phi \sim \text{Gamma}(0.1, 0.1) \tag{4.10}$$

Each model run consisted of four chains, each with 3,000 iterations and 1,500 warm-up runs; we used a thinning of every three samples and obtained a total number of 2,000 post-warmup samples. To assess whether the simulations converged, we checked the Gelman-Rubin potential scale reduction factor $\hat{R}$, which, if below 1.01, indicates that the Markov chains have converged (Kruschke, 2014). We also checked the effective number of independent samples N_{eff}, indicating lower autocorrelation and higher efficiency of the convergence (McElreath, 2016).

4.2.2.2 Model selection

We trained the models using several different combinations of predictors to find the best balance between complexity and predictive accuracy. Our main motivation was to achieve a good balance of sufficiently detailed, but available data, which is often challenging (Meyer et al., 2013; Molinari et al., 2020). Each predictor in a multilevel model requires more than one parameter (i.e. J group-level coefficients plus one hyperparameter). Hence, considering more parameters may offer small increases in predictive accuracy only at the risk of overfitting. We selected the model with the highest improvement compared to next simpler one, while retaining the same multi-level structure. On the one hand, testing all models possible without any underlying concept is far from good scientific practice and computationally inefficient; on the other hand, the predictors are rarely fully independent. Hence, we fitted candidate models in three steps of model comparison outlined below. We compare these models via the expected log pointwise predictive density (ELPD), which is the sum of a log-probability score of the predictive accuracy for unobserved data. The distribution of these unobserved data is unknown, but we can estimate the predictive accuracy with leave-one-out cross-validation (ELPD-LOO), which is the sum of the log-probability scores for the given data except for one data point at a time (McElreath, 2016; Vehtari et al., 2017). According to Vehtari (2020), an ELPD-LOO difference >4 may be relevant and should also be compared to the standard error of the difference. Hence, we selected models as follows:

1. We compared models with a gradually increasing number of predictors, based on the prior knowledge of predictor importance reported in a study using single-level linear regression by Mohor et al. (2020). This study considered water depth, for which data

are the most widely available and adopted in flood loss models (Gerl et al., 2016), up to a maximum of twelve predictors (Table 4.1). For example, model 2 (named "fit2") has water depth (WD) and building area (BA) as predictors, while model 3 ("fit3") has the previous two plus contamination (Con) as predictors; model 12 ("fit12") has all twelve predictors (Table 4.1). The model candidate with an ELPD-LOO difference >4 compared to the previous candidate was selected for the next step.

2. The model selected in step 1 – "fit_s1" - has a subset of the predictor matrix $\mathbf{X}$ with *s1* ($\leq K$) columns, i.e., $\mathbf{X}^{(s1)} = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_{s1}\}$. We then compared models with $\mathbf{X}^{(s1)}$ predictors plus one of the remaining predictors at a time, i.e., $\{\mathbf{X}^{(\mathbf{s1})}\}$, $\{\mathbf{X}^{(s1)}, \boldsymbol{x}_{s1+1}\}$, $\{\mathbf{X}^{(s1)}, \boldsymbol{x}_{s1+2}\}$, …, $\{\mathbf{X}^{(s1)}, \boldsymbol{x}_{12}\}$. All model candidates that present an ELPD-LOO difference larger than four and with a difference larger than its standard error were selected for step 3.

3. We compared the model candidates combining the selected candidates from step 2. If, for example, two different candidates $\{\mathbf{X}^{(s1)}, \boldsymbol{x}_{s1+a}\}$ and $\{\mathbf{X}^{(s1)}, \boldsymbol{x}_{s1+b}\}$ were selected, we compared the model candidates $\{\mathbf{X}^{(s1)}\}$, $\{\mathbf{X}^{(s1)}, \boldsymbol{x}_{s1+a}\}$, $\{\mathbf{X}^{(s1)}, \boldsymbol{x}_{s1+b}\}$, $\{\mathbf{X}^{(s1)}, \boldsymbol{x}_{s1+a}, \boldsymbol{x}_{s1+b}\}$. The model candidate with the least number of predictors and an ELPD-LOO difference >4 as well as a difference larger than the estimated standard error was selected eventually.

We compared all candidate models using leave-one-out cross-validation (LOO-CV) with Pareto smoothed importance sampling (PSIS-LOO), which is an out-of-sample estimator of predictive model accuracy (Vehtari et al., 2017), implemented in the `R` package `loo` (Vehtari et al., 2019).

Having identified the models with the most informative predictors, we checked for credible differences across levels using the 95% highest density interval (HDI) of the marginal posterior distributions of the model parameters. We refer to regression intercepts and slopes as *credible* if their posterior HDIs exclude zero values, and to each pair of parameters as *credibly different* if 95% of the distribution of the difference of posterior estimates is above (or below) zero.

4.3 Results

We begin by reporting results form the model selection where we aimed at a compromise between model complexity, predictive accuracy, and data availability. For example, the generic model (Equation 4.5) has the lowest complexity with one ($K = 1$) predictor water depth (thus called "fit1"), and three groups for the regional model ($J = 3$). This model has eight parameters already, i.e. the population-level intercept (α_0); three group-level

Table 4.3: Comparison of flood-type model candidates of differing complexity and using their expected log pointwise predictive density (ELPD-LOO), ranked by increasing predictive accuracy, along with differences and their standard errors with reference to model "fit1" (see Table B.1 for all model variants).

Model	ELPD-LOO	ELPD-LOO difference	Stand. error of difference	Predictors
fit1	2018.7	0	0	WD
fit2	2057.3	38.6	8.7	WD+BA
fit3	2093.2	74.5	12.5	WD+BA+Con
fit4	2098.1	79.4	12.8	WD+BA+Con+Dur
fit5	2113.4	94.7	13.6	WD+BA+Con+Dur+Pre
fit6	2124.0	105.3	14.1	WD+BA+Con+Dur+Pre+Ins
fit8*	2125.4	106.8	14.5	WD+BA+Con+Dur+Pre+Ins+Eff+Eme
fit10*	2125.9	107.2	14.8	WD+BA+Con+Dur+Pre+Ins+Eff+Eme+Cel+Vel
fit9*	2126.2	107.5	14.8	WD+BA+Con+Dur+Pre+Ins+Eff+Eme+Cel
fit7*	2127.0	108.3	14.5	WD+BA+Con+Dur+Pre+Ins+Eff
fit11	2131.8	113.1	15.1	WD+BA+Con+Dur+Pre+Ins+Eff+Eme+Cel+Vel+Exp
fit12*	2134.3	115.6	15.3	WD+BA+Con+Dur+Pre+Ins+Eff+Eme+Cel+Vel+Exp+BQ

* Difference between ELPD-LOO values between two subsequent models is <4

intercepts ($\boldsymbol{\alpha}_j$); three group-level coefficients for water depth ($\boldsymbol{\beta}_{1,3}$); and parameter ϕ. Candidate models with more predictors are more complex might fit the data better, but have a higher chance of missing input data at random. We test the increase in predictive capacity by adding predictors parsimoniously in light of this constraint.

4.3.1 Model selection

Judging from the predictive capacity using LOO-CV we arrived at a number of models worth further inspection. Table 4.3 shows how predictive accuracy in terms of the ELPD-LOO changes from the simplest water-depth model to eleven more complex candidates of the flood-type model (see Supplementary Material for other model variants). In this step, we consider a model to be significantly better if the difference of ELPD-LOO >4.

We find that models hardly improve beyond the complexity of model "fit6" (Table 4.3). Given that the choice of predictors may affect other predictors' contributions, we tested another set of models starting with the first six predictors but adding only one of the remaining predictors at a time, to evaluate if the order of adding predictors mattered (Table 4.4).

We find that "fit6+11" is the candidate model with the highest accuracy, though "fit6+7" is comparable (Table 4.4). We tested a final set of models with combinations of the best candidates, i.e. the predictors that showed significant increase among the further model candidates tested, namely predictors 6 (insured - Ins), 7 (perceived efficacy of PLPMs - Eff) and 11 (flood experience - Exp), added to the first five predictors (i.e. water depth, building area, contamination, duration, and Property-level Precautionary Measures (PLPM)). Note that fit5+6 equals fit6, but fit5+7 is not equal to fit7. The

Table 4.4: Comparison of the flood-type model candidates by their difference in ELPD-LOO using the first six predictors plus one predictor at a time, ranked by increasing predictive accuracy, along with their differences and the standard error of the differences with reference to the model "fit6" (see Table B.2 for all model variants)

Model	ELPD-LOO	ELPD-LOO difference	Stand. error of difference	Predictors
fit6+8	2122.3	-1.7	0.5	WD+BA+Con+Dur+Pre+Ins+Eme
fit6+10	2123.2	-0.9	1.4	WD+BA+Con+Dur+Pre+Ins+Vel
fit6	2124.0	0	0	WD+BA+Con+Dur+Pre+Ins
fit6+12	2124.2	0.2	2.0	WD+BA+Con+Dur+Pre+Ins+BQ
fit6+9	2124.4	0.3	2.0	WD+BA+Con+Dur+Pre+Ins+Cel
fit6+7	2127.0	3.0	3.5	WD+BA+Con+Dur+Pre+Ins+Eff
fit6+11 *	2130.8	6.7	3.9	WD+BA+Con+Dur+Pre+Ins+Exp

* model with relevant improvement compared to others (elpd_diff > 4 and elpd_diff > se_diff)

Table 4.5: Comparison of Flood-type model candidates by their difference in ELPD-LOO using combinations of the first five predictors (fit5) plus predictors 6, 7, and 11, along with their differences and the standard error of the differences with reference to candidate model "fit5+6" (see Table B.3 for all model variants)

Model	ELPD-LOO difference	Stand. error of difference	ELPD-LOO	Predictors
fit5+7	-6.2	6.1	2117.8	WD+BA+Con+Dur+Pre+Eff
fit5+11*	-3.5	6.4	2120.5	WD+BA+Con+Dur+Pre+Exp
fit6*	0	0	2124.0	WD+BA+Con+Dur+Pre+Ins
fit5+7+11*	0.1	7.4	2124.1	WD+BA+Con+Dur+Pre+Eff+Exp
fit6+7*	3.0	3.5	2127.0	WD+BA+Con+Dur+Pre+Ins+Eff
fit6+11	6.7	3.9	2130.8	WD+BA+Con+Dur+Pre+Ins+Exp
fit6+7+11	9.6	5.4	2133.6	WD+BA+Con+Dur+Pre+Ins+Eff+Exp

* models with predictive accuracy that is indistinguishable from that of the reference model fit6

results for the Flood-type model are shown in Table 4.5 (for other model variants, see Figure 4.1 or Table B.3).

Table 4.5 shows that two models are significantly better than "fit6" (fit5+6), i.e. "fit6+11" and "fit6+7+11". These two models are indistinguishable from each other in terms of their predictive accuracy, although model "fit6+11" has fewer predictors. We obtain similar results for other model variants (see Appendix B): for the regional model, "fit6+7" is also within the best candidates, while for the flood-event model adding more predictors hardly improves the predictive accuracy. In summary, we report that model "fit6+11" offered the best balance of complexity and performance among the model candidates considered.

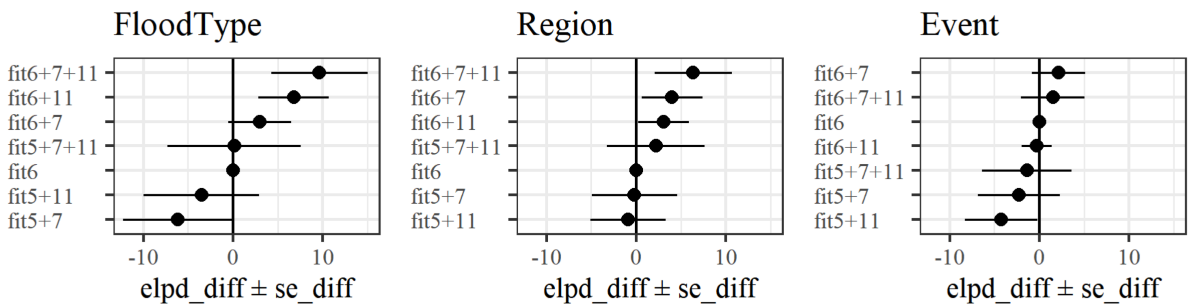

Figure 4.1: Comparison of model candidates by their difference in ELPD-LOO using combinations of the first five predictors (fit5) plus predictors 6, 7, and 11, along with their differences and the standard error of the differences with reference to candidate model "fit6" for each model variant

Table 4.6: Performance indicators over mean values of the posterior predictive distribution (median of performance indicators over the full posterior predictive distribution) and convergence indicators of the three model variants. RMSE = root mean squared error; MAE = median absolute error; $\hat{R}$ = Gelman-Rubin potential scale reduction factor; N_{eff} = effective sample size.

Model	Dataset	RMSE	MAE	highest $\hat{R}$	lowest N_{eff}
Flood-type model	Train	0.102 (0.138)	0.046 (0.053)	1.003	1236
	Test	0.108 (0.143)	0.044 (0.055)		
Regional model	Train	0.104 (0.140)	0.045 (0.054)	1.004	1273
	Test	0.110 (0.145)	0.045 (0.056)		
Event model	Train	0.103 (0.139)	0.045 (0.053)	1.004	1164
	Test	0.111 (0.144)	0.043 (0.055)		

4.3.2 Model diagnosis

We fit three multilevel models with the selected candidates (fit "6+11", i.e. water depth, building area, contamination, duration, PLPMs, insured, flood experience) in each of the flood-type, regional, and event model. All three multilevel models converged ($\hat{R}$ < 1.004) with effective sample sizes N_{eff} from 1164 to 1273 (out of 2000 samples). The multilevel model was trained with 70% of the dataset that was drawn through random sampling maintaining the proportion of group levels, totalling 1269 data points without missing data. The remaining 30% of the data were used for a performance check (Table 4.6).

We also ran posterior predictive checks by comparing the observed distribution of the loss ratio with the posterior predictive distribution drawn from the training and the test data (Figure 4.2). The shapes of the posterior predictive distributions align well with the observed data, indicating that the models suitably simulate the response variable.

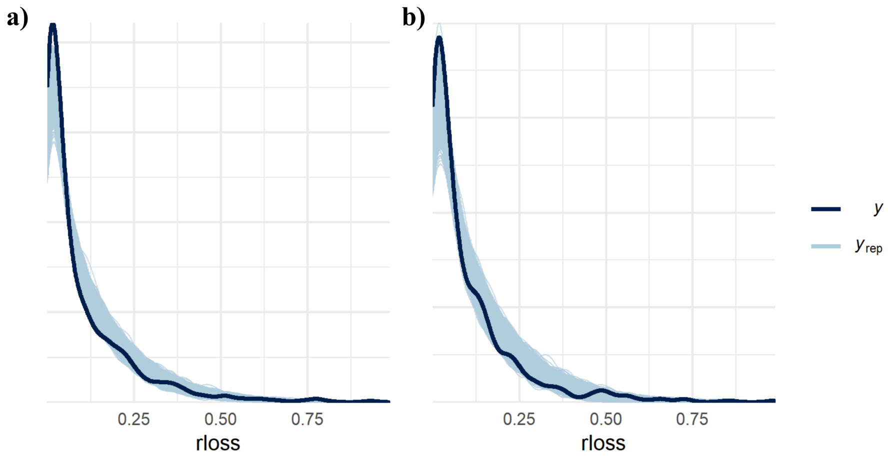

Figure 4.2: Density plot of observed loss ratio (y) and simulations drawn from posterior predictive distribution (y_{rep}) over a) training ($n = 1269$) and b) testing ($n = 543$) data with flood-type model

4.3.3 The roles of flood type, affected region, and flood event

In this section we show the group-level coefficient estimate intervals of each model and whether they are credibly different for different groups. We report the highest density interval (HDI) of the posterior model weights and compare these estimates between the groups of each model. The models use a inverse-logit transformation over the linear regression (Equation 4.5) to transform any real value to the unit interval. For example, a population-level intercept $\alpha_0 = -2.37$ means that, holding all predictors fixed at zero (or their average), $\text{logit}^{-1}(-2.37 + 0) = 0.085$; hence the estimated average loss ratio is 8.5%. Positive (negative) coefficient estimates of each predictor will result in a larger (smaller) loss ratio from the average on the log-odds scale.

4.3.3.1 Flood-type model

Figure 4.3 shows the 95% HDI of the predictor weights grouped by flood types (flood-type model) compared to that of the pooled model. The groups of surface water and groundwater flooding have fewer data (levee breaches, $n = 258$; riverine $n = 683$; surface water $n = 152$; groundwater $n = 176$) and thus more uncertain parameter estimates with wider HDIs (Figure 4.3), although several of these estimates are credible. Six out of seven predictors, i.e. water depth, contamination, duration, PLPMs, insured, and flood experience, have at least one pair of flood types with credibly different estimates. In these cases the 95% HDI of the differences between the posterior estimates is above or below zero. Most estimates are credibly positive or negative, and only a few estimates 95% HDI contain zero.

For example, the standardised group-level intercepts ($\alpha_0 + \alpha_j$) that estimate the loss ratio for average predictor values, are credibly smaller for groundwater floods than for

Table 4.7: Credibly different pairs of estimates with 95% probability

Comparison	Predictor	Median of differences	% above 0
Levee Breach-Groundwater	Intercept	0.323	99.4%
Riverine-Groundwater	Intercept	0.212	98.6%
Surface-Groundwater	Intercept	0.210	96.7%
Levee Breach-Surface	Water Depth	0.155	98.4%
Riverine-Surface	Contamination	-0.167	1.6%
Riverine-Groundwater	Duration	0.114	95.2%
Levee Breach-Riverine	PLPMs implementation	0.162	99.0%
Levee Breach-Surface	PLPMs implementation	0.207	98.6%
Levee Breach-Riverine	Insured	0.107	96.7%
Levee Breach-Surface	Insured	0.213	99.6%
Levee Breach-Groundwater	Insured	0.186	98.9%
Levee Breach-Surface	Flood Experience	-0.228	0.6%
Levee Breach-Groundwater	Flood Experience	-0.195	1.9%
2002-2005	Intercept	0.521	100.0%
2002-2006	Intercept	0.448	98.7%
2002-2010	Intercept	0.261	99.6%
2002-2011	Intercept	0.612	99.9%
2005-2013	Intercept	-0.517	0.2%
2006-2013	Intercept	-0.447	1.2%
2010-2011	Intercept	0.346	95.2% *
2010-2013	Intercept	-0.259	0.7%
2011-2013	Intercept	-0.609	0.1%
2002-2005	Water Depth	0.343	99.5%
2005-2010	Water Depth	-0.369	0.7%
2005-2013	Water Depth	-0.394	0.2%
2011-2013	Water Depth	-0.259	3.1% *
2002-2010	Duration	0.175	98.7%
2002-2010	PLPMs implementation	-0.179	1.8%
2005-2013	Insured	-0.157	4.5% *

* Although the one-sided hypothesis is satisfied, with 95% of the posterior distribution being above, or below, zero, the 95% HDI of the distribution of the differences contains zero

other flood types. Water depth has a credibly higher weight for levee breaches, i.e. the effect of each unit increase in water depth on the loss ratio is higher for levee breaches, than for surface water floods (Figure 4.3-b, Table 4.7). In most cases, the differences show a higher effect of levee breaches over other flood types. The contamination effect of surface water floods is also credibly higher than of riverine floods, and the effect of riverine flood duration credibly outweighs that of groundwater-flood duration.

The effects of flood duration (Figure 4.3-e), the insurance indicator (Figure 4.3-g), and the flood-experience indicator (Figure 4.3-h) remain inconclusive concerning surface water or groundwater floods. Similarly, flood PLPMs implementation (Figure 4.3-f) is an ambiguous predictor of relative loss caused by levee breach or groundwater floods.

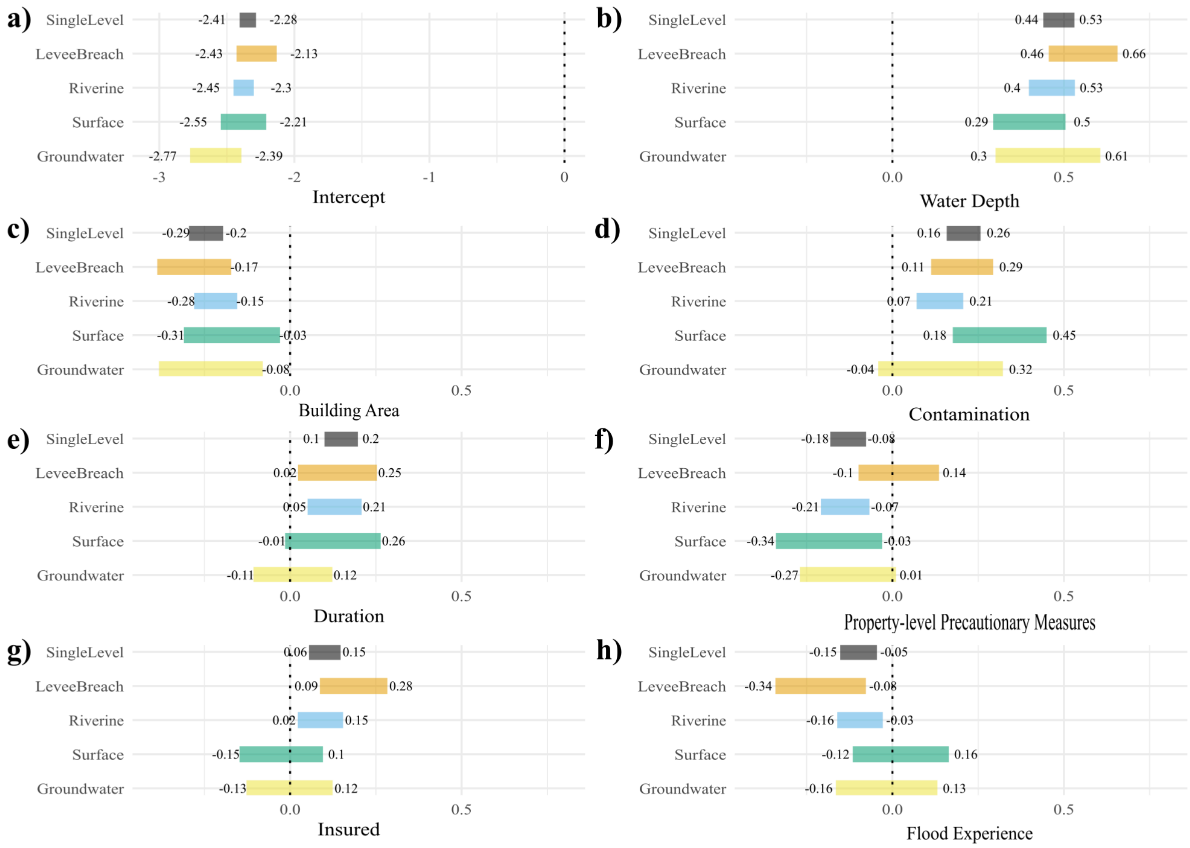

Figure 4.3: 95% HDI of regression estimates of the Flood-type model (across four flood types, coloured segments) and the single-level model (black segments). The intercept is the sum of the population-level effect (common across levels) and group-level effects (for each flood type)

4.3.3.2 Regional model

Figure 4.4 shows the 95% HDI of the regression coefficients if we group the loss data across various regions of Germany. The group of flood-affected households from western and northern Germany is the smallest (south $n = 337$; east $n = 865$; west and north $n = 67$), so the posterior parameter estimates are less certain and, in most cases, inconclusive for this part of the country.

Similar to the flood-type model, all estimates are credibly different from zero for water depth (Figure 4.4-b). The HDIs of all predictors overlap, i.e. there are hardly credible difference across regions under this model. The only estimate that is ambiguous in the southern region is that for flood experience (Figure 4.4-h).

4.3.3.3 Event model

Figure 4.5 shows the 95% HDI of the posterior regression weights if grouping the data across individual flood events indexed by years. The data subsets of flood-affected households in 2002 and 2013 are largest, (2002, $n = 571$; 2005, $n = 56$; 2006, $n = 30$;

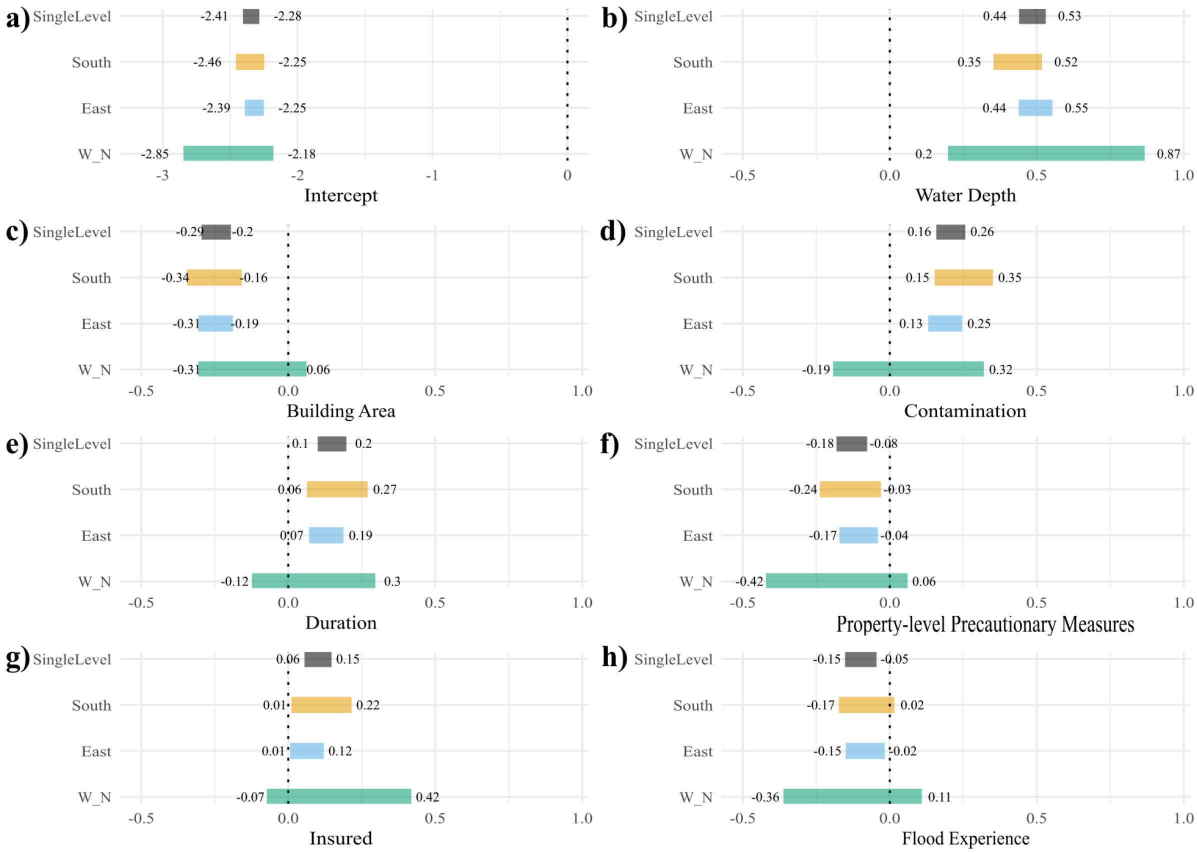

Figure 4.4: 95% HDI of regression estimates of the Regional model (across three regions, coloured segments) and the single-level model (black segments). The *Intercept* is the sum of the population-level effect (common across levels) and group-level effects (for each region)

2010, $n = 141$; 2011, $n = 66$; 2013, $n = 405$), hence their estimates are more certain than those for other events. Similar to the results of the regional grouping, we notice a large overlap of parameter estimates across individual floods without credible differences.

Estimates of the intercept (Figure 4.5-a) are highest for 2002 and 2013, whereas the other, lower estimates overlap, except for 2010 and 2011 that are also distinct from each other (Table 4.7). This result underlines that the floods of 2002 and 2013 were more damaging than other events on average.

The 95% HDI of estimates of water depth (Figure 4.5-b) for 2002, 2010, and 2013 are credibly higher than for 2005. The HDI for 2013 is also credibly higher than that for 2011, while other pairs of estimates overlap (Table 4.7). The coefficient estimates for duration and the PLPMs implementation (Figure 4.5-e and -f) for 2002 surpass the estimates for 2010, which in turn are ambiguous. The estimate for the insurance indicator of 2013 exceeds that for 2005, although all 95% HDIs except for the one for 2013 contain zero. We note that many parameter estimates cover mostly small values; especially flood experience (Figure 4.5-h) is an inconclusive predictor in contrast to the other models

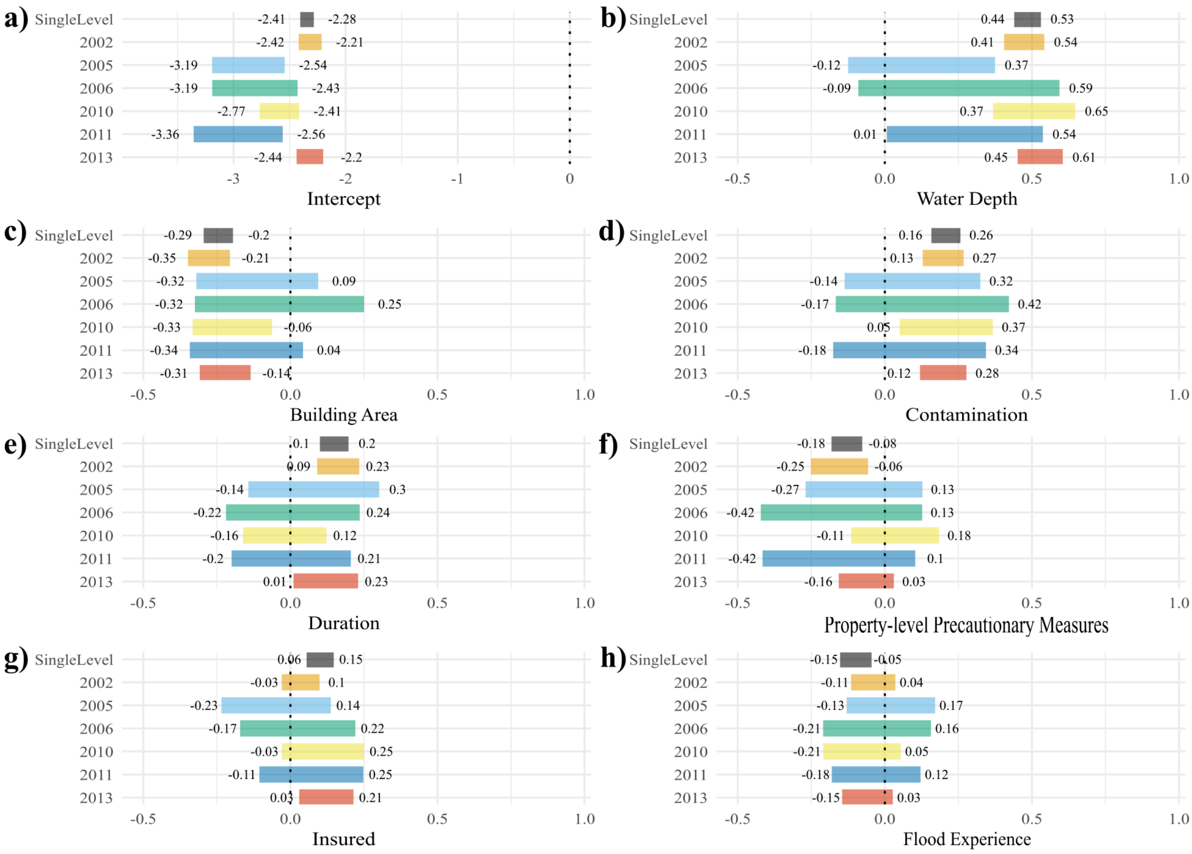

Figure 4.5: 95% HDI of regression estimates of the flood-event model (each event coded by colour) and the single-level model (black bars). The intercept is the sum of the population-level effect (common across levels) and group-level effects (for each event)

(Flood-type model or Regional model) that showed credible estimates for at least one group. There is no clear tendency of estimates increasing or decreasing with time; on the contrary, there is a large overlap across most events and predictors.

4.4 Discussion

We trained three variants of a Bayesian multilevel model to test whether flood type, regions within Germany, or flood events make a case for differing predictor influences on flood loss concerning these groups. The models help us to identify the factors most relevant for flood loss estimation and to assess whether there are credible differences between these contributions to the estimated loss ratio. In other words, the models show how considering these groups is a useful step towards improved model transferability.

After comparing the predictive accuracy estimates of models with different sets of predictors, we selected the model "fit 6+11" that uses water depth, building area, contamination, duration, PLPMs, insurance, and previous flood experience as predictors. Considering that we aim to explore the role of predictors in estimating flood losses, rather than finding the best fit model, chains convergence and posterior predictive checks are a necessary step before interpreting the fitted model (Gabry et al., 2019; Gelman et al., 2020). The three model variants trained with 1269 datapoints, and sampled with four chains each, converged well, with Gelman-Rubin scales below 1.004 (ideal values are $<$1.01) and effective sample size ratios above 0.58 (ideal values are $>$0.5). Visual assessment is an important step to check whether the model generates data similar to the observed data. Figure 4.2 shows that the model replicates well the data distribution, and visual inspection confirmed only unimodal estimates.

Our results show that, for most cases across regions or across flood events, the posterior regression weights are hardly different. Therefore, distinguishing groups, at least in the form here implemented, adds little information over a pooled model taking into account all of the data. Out of the training dataset of 1269 data points, the groups contained much smaller ($<$200 to $<$50) samples, thus giving rise to higher uncertainties regardless of the shrinkage of coefficient estimates in a Bayesian multilevel model towards the pooled means. Credible differences across estimates are found mostly if considering flood types and this grouping also involves more balanced subsets. The estimated coefficients for loss-ratio modelling across flood events and regions are mostly inconclusive. However, especially in western and northern Germany, the 2005, the 2006, or the 2011 flood events return many inconclusive parameter weights, likely owing to the much fewer data points. Leaving these very uncertain estimates aside, we can observe several instructive patterns.

We note that the higher the water depth, the contamination of the floodwater, or the duration a building is inundated, the higher is the loss ratio, assuming all other predictors fixed. This is a simple expectation (Kellermann et al., 2020) being confirmed, also showing that these predictors add information to the model (see Figures 4.3, 4.4, 4.5-b and -e). Next, the larger the building, the lower the relative damage. This is also reasonable, since larger buildings, which mostly have more floors, would experience lower relative damage with all else kept constant (Thieken et al., 2005). We also find that the more recently a household experienced a flood, the lower the relative damage. People who experienced more recent floods (scored higher in the flood-experience indicator), on average, appear to be better acquainted with how to act before and during a flood, thus reducing its risks and direct impacts. The indicator of whether the household had an insurance has mostly positive weights, although often also ones that are ambiguous. This result is in agreement with previous studies showing an unclear effect of insurance coverage on loss reduction (Surminski & Thieken, 2017). Finally, the indicator of PLPMs implementation also has a mostly negative weight on predicting the loss ratio. This may mean that the more PLPMs implemented, the lower the relative damage, as shown by Kreibich, Thieken, Petrow et al. (2005) and Hudson et al. (2014). However, this indicator encompasses several measures so that the damage reducing effect of each such measure in different flood situations is intractable. Hence, this result only shows a general tendency that PLPMs reduce relative damage, but to a much-varied degree that deserves further research.

Although previous work has indicated a more intense flood events in eastern than in southern Germany, except for the 2005 flood (Schröter et al., 2015), we found no credibly different estimates in our regional model (Figure 4.4). It is likely that different precaution strategy of residents matter here, as more people in the East have relied on insurance (Thieken, 2018), although the effect of having insurance on flood losses remains unclear; the effect of PLPMs also overlaps across estimates for southern and eastern Germany.

Despite the large overlap across estimates of the flood-event model, we find that the estimates for 2002, 2010, and 2013 for water depth and contamination are larger and more credible, reflecting also larger average losses reported by the households (Table B.4). Although the 2006 subsample had a large average flood duration (Table B.4), it still returns a highly uncertain coefficient estimate. The severe Central European flood of August 2002 in Germany mainly affected the rivers Danube and Elbe, and only a few households had implemented PLPMs or had previous flood experience (Thieken et al., 2007); this situation changed for later floods (Kienzler et al., 2015). Consequently, the implemented PLPMs made a larger difference for the flood of 2002 (the only credible estimate), whilst the role of previous flood experience remains ambiguous in the models. In contrast, as insurance coverage increased over time, only the 2013 estimate was credibly positive; having an insurance seems to be linked to a higher loss ratio. This finding that insurance has a positive effect—though only for the later event—may indicate that either moral hazard has increased (i.e. insured people declare more damage) or that more people in risk-prone areas have purchased insurance coverage against flooding. The latter would indicate that risk communication was partly successful. To confirm this, however, not only would the increase in insurance uptake need to be checked, but it would also need to be crossed with flood risk zones. This is a task for future work.

We emphasise that each event and each region of Germany contained mixed flood types (or pathways). For most predictors, the factors' effects are much clearer across flood types. This reinforces the notion that their importance varies across flood types. Given that mixed flood types were reported in all regions and years in our dataset, this might be the reason the predictors effects are also less certain and overlapping across regions and years.

It is plausible that the effects of some variables are influenced by others, whether included or ignored in our initial set. Only a few studies have so far directly compared the effect of predictors of flood loss ratio across groups in the data, such as flood types, events, or places. Two of them, i.e. Vogel et al. (2018) and Sairam et al. (2019), used a similar dataset. Although these studies adopted different model structures, we compare below our results.

Sairam et al. (2019) trained and compared hierarchical Bayesian models for flood loss estimation as we did here, but they considered only water depth as a single predictor. Sairam et al. (2019) tested as grouping variables the river basins, the event years, and a combination of both, and concluded that the latter had the best predictive accuracy. This approach, however, masks the weight of effects across areas or events, as both effects are bundled. Despite the differences in the grouping, similarly, Sairam et al. (2019) found significant differences between regression slopes, but not across intercepts, reinforcing that using flood type as grouping variable seems to be more relevant compared to flood event or region.

Vogel et al. (2018) trained Markov Blankets (MBs) for estimating the flood loss ratio for different flood types and different events, separately. MBs are the smallest components of Bayesian Networks (BNs) and contain all variables that are relevant, out of the originally chosen, for predicting the targeted variable (Vogel et al., 2018). Therefore, we cannot compare estimates, but only the predictors set selection. We selected the predictors across all levels, which makes a direct comparison difficult, trained independently. Still, we observe some similarities between ours and the results by Vogel et al. (2018). For example, Vogel et al. (2018) showed that previous flood experience and flood duration are both relevant for households affected by levee breaches, whereas building size, which is correlated to building area, is relevant for riverine floods. For the MBs trained for each flood event, Vogel et al. (2018) found water depth to be a common predictor for all events, except for the flood of 2011, which comprises one of the smallest subsamples, in which previous flood experience was the only predictor selected, in contrast to our findings. Our very uncertain estimates across event years for this predictor suggests it may be biased and deserve more attention before dismissing all estimates with HDI containing zero. More data should be collected or predictors could represented differently, for example as a monotonic effect.

Data availability, especially regarding preparedness indicators, is a possible limitation to transferring flood loss models and their use for ex-ante loss estimation. While these indicators have been deemed relevant for loss prediction, they are rarely collected and are often unavailable in a suitable form. An alternative is to use proxy data, for example the aggregated insurance coverage for Germany monitored by the German Insurance Association (Gesamtverband der Deutschen Versicherungswirtschaft, 2018) as proxy for household insurance, a good flood event database could be a rough estimate of flood experience for a specific region, or the precautionary behaviour of flood-affected residents (Bubeck et al., 2020) could be used as a prior estimate of PLPMs implementation. Nonetheless, the role of data availability is directly captured in our models in terms of (un-)certainty of posterior parameter estimates. Bayesian models excel in situations where data are limited, but also express the associated uncertainties.

When addressing transferability, we seek models that can generalize well and go beyond local or case-specific data. Wagenaar et al. (2018) trained two flood loss models using data from two different countries (Germany and the Netherlands) and tested how well each model could predict losses in the other country. They found that the number of flood events in the data was more important than simply the number of reported flood loss cases. Although we trained our models with data from a single country, the data used by Wagenaar et al. (2018) for Germany, comprises six event years across twelve federal states, four river basins (Danube, Rhine, Elbe, and Weser) and four flood types. We expanded on this approach by training models on data from different flood-event years, different flood types, and different regions, thus allowing for a broad range of environmental, administrative, and socio-economic conditions (representing at least Central Europe) that we treat explicitly as grouping levels in our analysis. We argue that exploring these model variants provides more clarity about whether we should use simple average models or more specific multi-level models to be able to transfer predicted loss estimates to new regions, flood types or other structures in the data.

4.5 Conclusions

Previous studies have indicated that the major damaging processes during floods may differ by flood type, event, and affected region. To better understand these differences and improve the transferability of flood loss models, we trained and tested Bayesian multilevel models for estimating relative flood losses to residential buildings.

Our model selection identified seven predictors addressing the flood magnitude (water depth, contamination, and duration), the building size (building area), and preparedness of the household (previous experience, insurance, and an indicator of implemented PLPMs). For at least one group, all predictors show credible posterior estimates 95% HDI. This result confirms that all these predictors can aid flood loss ratio estimation, and reinforces the need to collect data after new flood events. This repeated updating is at the core of Bayesian models, which can also handle missing data, account for uncertainty intrinsically, and are effectively finding a compromise between existing models and new data. We argue that this strategy might pave one way for transferring flood loss models more widely.

Credibly different estimates were found for six out of seven predictors across flood type, region, and event year, namely: water depth, contamination, duration, implementation of property-level precautionary measures, insurance, and previous flood experience. The Bayesian multilevel model grouped by flood type is the most informative of these three model variants, featuring the most pronounced differences in the contributions of each predictor. Despite credible differences between different flood events, the large uncertainties in the posterior estimates of the regional and the event models likely indicate that several flood types may have mixed during a single flood event or region, thus making it difficult to disentangle individual controls better. In any case, the dataset hardly caters to reveal fully the underlying physical controls on flood losses.

Our results encourage using pooled data on flood events and regions, and thus mark some transferability in this regard, judging from the minute differences in the posterior regression weights. The data indicate, however, that flood loss modelling should consider different flood types explicitly. We acknowledge that other groups in the data or a different set of predictors could improve predictions further, but recommend strategies that make use of previous knowledge as much as possible. We conclude by reporting that grouping models by flood type adds information and transferability to flood loss estimation and motivate more research into this direction.

Acknowledgements

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Chapter 5

Estimating the Financial Loss of Residential Buildings under Compound Inland Floods [1]

Abstract Rainfall-triggered floods are usually classified into pluvial or fluvial floods. Yet combinations of flood types and processes are more diverse, with many possible pathways between the rainfall and elements at risk, such as residential buildings. Hence, multiple flood pathways that impacted a given building were reported in the aftermath of floods. The resulting compound impacts might compromise flood loss estimation when using prediction models that fail to consider multiple flood pathways and the differences in damaging processes. We estimate compound inland flood losses by learning Bayesian multilevel models that consider multiple flood pathways modelled as (1) multiple memberships, and as (2) combined categories. We find that acknowledging multiple pathways in the models credibly alters parameter estimates for each flood pathway, whereas none of the cases considered showed credibly that compound flood-loss estimates are larger than the average of their composing single flood pathways. Improvements to flood-loss estimation may require non-linear or mixed models instead. Especially for the compound cases, hydraulic models might better inform loss models, but the case-by-case use of such models remains impracticable.

[1] This chapter has been submitted and is currently under review as Mohor, G. S., Thieken, A. H., & Korup, O.: Estimating the Financial Loss of Residential Buildings under Compound Inland Floods

5.1 Introduction

Research on natural hazards has increasingly addressed compound events, i.e., multiple hazards that coincide in space and time or happen sequentially, causing multiple, severe impacts (Liu et al., 2015; Luo et al., 2020). Zscheischler et al. (2020) suggest a classification of compound events into: preconditioned events, when a certain previous (climate-driven) condition leads to or amplifies the hazard's impact; multivariate events, when multiple hazards coincide in the same area; spatially compound events, when several places are impacted by the same hazard or the same triggering event; and temporally compound events, when hazards - usually triggered by a common climatic driver or by a different hazard- happen sequentially, also termed cascading events (Zuccaro et al., 2018).

In a risk assessment framework, 'pathways' form the state variable that links the source (the hazard) to the receptor (the affected asset or element at risk) (Hall et al., 2003; Sayers et al., 2002). In the context of floods, pathways are, for example, urban drainage systems whose capacity is exceeded due to heavy rainfall, the overflowing of riverbanks, or surfaces where excessive rainfall translates into pronounced runoff. We refer to a flood as compound flood if several pathways occur simultaneously or sequentially in the same flood event. For example, Macdonald et al. (2012) studied a groundwater flood risk in Oxford, UK, identifying areas affected by groundwater far from the river banks, and areas where both flood pathways (groundwater and river floods) act together; similarly, Chen et al. (2010) showed (for Bradford, UK) that urban environments can be affected by compound urban and river flood, where urban floods are the surface water floods caused by stormwater exceeding the urban drainage system capacity.

Survey data of flood-affected households in Germany (Thieken et al., 2017; Thieken, Mohor et al., 2021) and flood reports (Bavarian Environment Agency, 2007; Belz et al., 2006; Booß et al., 2011; Bronstert et al., 2018; Freudiger et al., 2014; Gesamtverband der Deutschen Versicherungswirtschaft, 2015; Kreibich et al., 2009; Rözer et al., 2016; Schröter et al., 2015; Ulbrich et al., 2003) confirm that several inland flood events might be characterized as (spatially) compound events (IPCC, 2012; Zscheischler et al., 2020). Furthermore, several households reported being affected by more than one flood pathway in the same event (Kreibich et al., 2009). However, the requirements for modeling financial losses arising from such compound inland floods have yet to be examined. On the one hand, the separation of damage per source is at times a requirement for insurance purposes (Baradaranshoraka et al., 2017). On the other hand, compound events may lead to impacts greater or smaller than the sum of individual hazards, as single-hazard models are not able to capture potential synergetic effects (Kappes et al., 2012; Liu et al., 2015; Luo et al., 2020). For example, Huang et al. (2021) showed that summing up estimates from individual factors can lead to overestimation of 20% of the hazard flood water depth.

To our knowledge, this is the first study to estimate the financial loss of compound inland floods, i.e., how they contribute to the overall loss.

Our modelling approach recognizes that different flood pathways may involve different damaging processes, driven, for example, by flow depth, velocity, debris concentration, and the presence of contaminants in floodwaters (Kelman & Spence, 2004). Such hazard characteristics, together with levels of flood preparedness, may differ significantly between flood pathways (Mohor et al., 2020; Thieken, Mohor et al., 2021), and influence models of flood losses (Mohor et al., 2020; Vogel et al., 2018). For groundwater flooding, for example, Kreibich and (Thieken et al., 2008) found that a pathway-specific loss model was able to model damage better than a general flood loss model. Therefore, we distinguish in this study between floods that, although caused mainly by intense or prolonged rainfall, develop through distinct pathways, namely: levee breaches, river floods, surface water floods, and groundwater floods. Coastal floods, usually caused by high tides or storm surges, are not considered in this study.

Building upon previous work that showed that differences across flood pathways should be considered for better loss estimation (Mohor et al., 2020; Mohor et al., 2021; Sairam et al., 2020; Vogel et al., 2018), our study has two goals: i) to integrate mixed effects from coinciding flood pathways that impacted individual residential properties to improve the estimation of each single-flood pathway effect, and ii) to assess whether there is an added loss under such coinciding flood pathways. We trained Bayesian multilevel models (BMM) on flood survey data, learning different parameters for each group (i.e. flood pathway) in the data, while allowing that groups learn from each other. We trained four BMMs variants under two different structures that allow for i) a "multi-membership", i.e., a given affected building can be assigned to more than one flood pathway, and ii) categories of each combination of flood pathways.

5.2 Data and Methods

5.2.1 Data set and flood pathway assignment

Surveys of German households affected by various floods have been collected via Computer-Assisted Telephone Interviews - CATI (Kellermann et al., 2020; Thieken et al., 2017). These surveys comprised about 180 questions, with slight adaptations after each campaign, but in way that most of the variables remained comparable over time. Surveys were undertaken seven months after each flood at the earliest, giving time for the interviewed households to evaluate their financial losses from the repair or replacement of the building components and contents. Here, we only address the direct damage to the structural components of the building. The surveys addressed several aspects of the

Table 5.1: Description of predictor variables in Bayesian models of flood-loss estimation

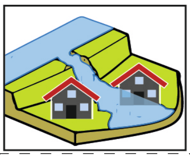
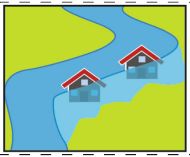
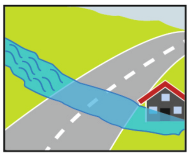
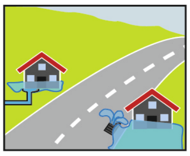
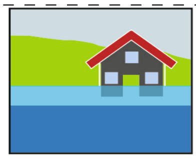
Variable	Unit	Description (transformation before modelling)	Reported raw values (n=6000)
Water depth	cm	Flood water depth above ground level (standardized*)	-470 – 1328
Building area	m^2	(Natural Log-transformed and standardized*)	30 – 18,000
Contamination	-	Indicator from 0 (none) to 2 (heavy contamination)	0 – 2
Duration	h	(Natural Log-transformed and standardized*)	0 – 2376
Property-level Precautionary Measure (PLPM)	-	Indicator from 0 (none) to 2 (very good precaution)	0 – 2
Insured	y/n	Policyholder of a flood insurance before the event	y/n
Flood experience	-	Classes from 0 (no previous flooding) to 4 (more often and more recent previous flooding)	0 - 4

damaging process: hazard characteristics (such as the depth and contamination of flood waters), warning, preparedness (such as previous experience and risk awareness), response, socioeconomic information, and impacts, both financial and psychological. The dataset comprises more than five thousand entries (with 2911 valid building loss ratios) from 14 out of 16 federal states after eight floods between 2002 and 2016.

Previous work has studied this surveyed information to learn which variables are significant for estimating financial losses (loss ratios) of the residential buildings (e.g. Kreibich, Thieken, Petrow et al. (2005), Merz et al. (2013) and Thieken et al. (2005)), and a detailed description of the selection of potentially explaining variables is found elsewhere (Merz et al., 2013; Mohor et al., 2020; Vogel et al., 2018). Mohor et al. (2021) used a Bayesian multilevel framework to select seven predictor variables with different grouping variables, balancing model complexity and prediction accuracy. We adopt the same set of predictors (Table 5.1).

In the surveys, the households also answered the question "To which process do you attribute the flooding of your property?". Eight different response options were provided to the interviewee, and multiple items could be chosen, including custom descriptions, if so preferred. Table 5.2 shows the reclassification of the responses into commonly used categories of flood pathways (Gradeci et al., 2019; Macdonald et al., 2012; Thieken, Mohor et al., 2021). These answers addressed, in layperson's terms, the pathways through which

Table 5.2: Flood pathways description in the surveys and their categorization

Response option provided in the questionnaire	Categorized flood pathways	Illustration
Breach of a dam, dike, or retention body	Levee breach	
Overflow of water body (nearby creek, river, or streamflow overtopped its banks)	River flood	
Surface water running wild from roads or slopes		
The sewage system could no longer divert the water from the street		
Failure of drainage on own property*	Surface water flood	
Open answer, most of which reflected heavy rainfall		
The water entered the house directly through drains or toilet		
Rising groundwater	Groundwater flood	

* Asked only after the 2014 and 2016 flooding events

the flood waters reached or entered the house, reflecting the dynamics of the physical process. The direct translation of immediate observations to actual flood pathways is however not completely unambiguous. For example, the interviewees' report in the 2013 survey and levee breaches have been cross-checked (not published) and showed good agreement, raising trust in the households' observations. However, the distinction of surface water flood pathway from an overflowing water body or between rapid- and slow-onset events is sometimes vague without further technical analysis. Therefore, flash floods and urban floods were not further separated, but classified as surface water flooding (Table 5.2).

The first survey campaign after the 2002 flood event did not pose the same question but simply asked about the direction of flood pathways. From this survey, we extracted the flood pathways based on a combination of channel size (river or creek) and other specific information such as: Levee breaches that were searched in the aftermath of the flood (Hristova, 2007) and assigned to the cases based on geocoded information; riverine floods, when the flood happened near large or mid-sized rivers or selected smaller river channels (for example "Vereinigte Mulde" and "Vereinigte Weisseritz); surface wa-

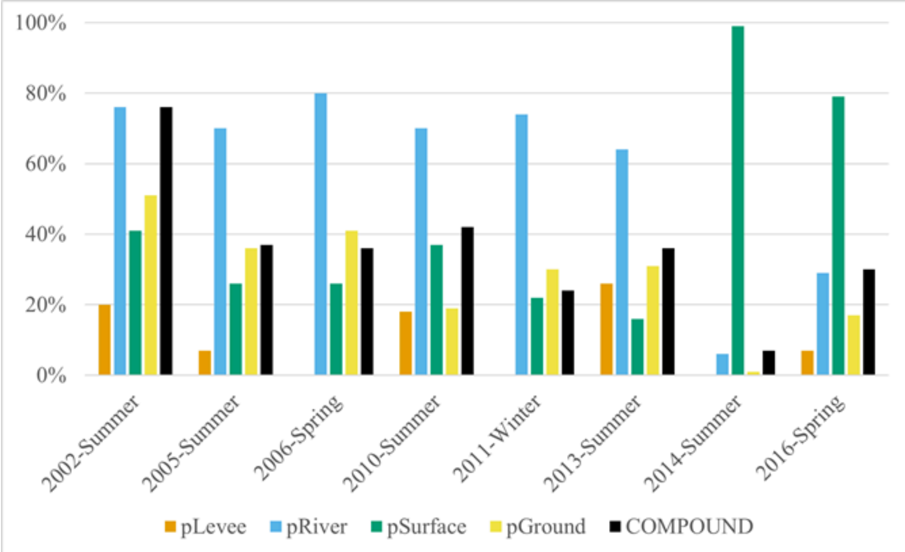


Figure 5.1: Flood pathways reported in each of the surveyed compound inland flood events

ter floods, with the movement of boulders, through channelization (equivalent to 'The sewage system could no longer divert the water from the street'), through rainwater or surface runoff (equivalent to heavy rainfall), or from small and selected creeks (for example "Floeha", "Gottleuba", "Grosse Striegis", "Mueglitz", "Lungwitzbach"); or groundwater flood, when water entered the building from below.

Coinciding different flood pathways were reported in all surveys, so that we treat these coincidences as compound inland flood events (Figure 5.1). These include preconditioned events, such as the excessive rainfall on already saturated soils resulting in widespread river flood and groundwater floods in the summers of 2002 (Ulbrich et al., 2003), 2005 (Kienzler et al., 2015), spring of 2006 (Kreibich et al., 2009), and the summer of 2013 (Schröter et al., 2015); and rain-on-snow floods in the spring of 2006 (Belz et al., 2006) and the winter of 2011 (Freudiger et al., 2014), a typology that leads mostly to large riverine floods, but also led to multiple pathways. Multivariate events (Zscheischler et al., 2020) have been reported in the summer of 2005 (Rözer et al., 2016), when urban drainage system capacity was overloaded and several creeks overtopped at several municipalities. Spatially compound floods were also reported in the summers of 2002 (Ulbrich et al., 2003), 2010 (Kienzler et al., 2015), and 2013 (Schröter et al., 2015), when several catchments of Germany flooded at the same time and nearby levees breached or were overtopped. The flood events of summer 2014 (Spekkers et al., 2017) and spring 2016 (Bronstert et al., 2018) were predominantly surface water floods, but other flood pathways were reported, too. In particular, flash floods occurred in small to medium-sized catchments.

A summary of all compound cases, i.e., cases that reported more than one pathway, is shown in Figure 5.2. We removed the unlikely and less informative combination of all flood pathways ('Levee and River and Surface and Ground', n=40 cases), two least reported combinations that includes levee breaches and groundwater flood pathways without the connection with a river flood ('Levee and Surface and Groundwater', n=18; and 'Levee and Groundwater', n=9), as well as cases where no flood pathway was reported (n=6). For the modeling task, we split the data between a training data set, with a total of 1717 data points from the surveys after the floods of 2010, 2011, 2013, 2014, and 2016, and a test data set, after the flood events of 2002, 2005, and 2006, summing up to 1153 cases.

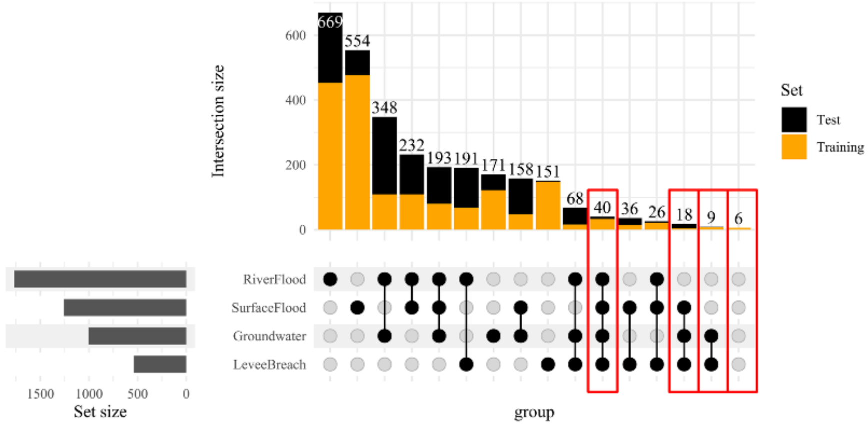


Figure 5.2: Compound inland floods datapoints. Removed combinations are in red boxes

5.2.2 Bayesian multilevel modeling

Most flood-loss models reflect the assignment of a flood event to a single flood pathway, even if different processes (pathways) took place. Thus, different models were developed for different flood pathways, assuming that the damaging processes were disconnected from each other. With few exceptions, such as the MCM (Penning-Rowsell, 2005) and HAZUS (Scawthorn et al., 2006) models that use different depth-damage curves for fluvial or coastal floods, most loss models were developed considering a single (riverine) flood pathway (Gerl et al., 2016), assuming that flood events, and the respective loss data used to calibrate the models are of a single pathway.

The potential roles of different damaging process can be lost when a loss model disregards the structure in the data and subsamples, for example when different flood pathways are modeled fully bundled (complete pooling) or fully separated (no pooling) (McElreath, 2020). Introducing more predictor variables to the flood estimating model increases model performance but also model complexity, challenging model fitting. Therefore, we explore BMMs that integrate different flood pathways at the same time. We choose a partial pooling modeling approach (multilevel model) that mirrors the structure in the data (in our case, flood pathways), in which each group learns from the other groups, virtually increasing the amount of data used for learning the model (McElreath, 2020). In the

Bayesian approach, parameters are understood as random variables. In Bayesian models, probabilities are manipulated to make inferences about the parameters of a model instead of the data. To find out a probabilistic description of an unknown parameter of a model we use (i) a prior belief or knowledge about the parameter encoded as a probability distribution; and (ii) a likelihood function – a conditional probability function of observing the data under a given set of parameter values. The normalized product of these two elements defines the posterior distribution, i.e., the trained joint probability of the parameter values given the observed data, with all uncertainty incorporated (Gelman et al., 2014; Kruschke, 2014; McElreath, 2020).

BMMs allow for partial pooling of the data and learn different parameters for different groups in the data keyed to flood pathways. The learning process refers to all parameters simultaneously, and increases statistical power (Gelman et al., 2014; McElreath, 2020). BMMs are very capable and adaptable, accommodating several distribution families, variable types (metric or non-metric), and multilevel or nested structures to reflect groups in the data. In our study, the posterior distribution is numerically approximated with the probabilistic programming language Stan (version 2.26; Stan Development Team (2019)) implemented in the package brms (version 2.14; Bürkner (2017)), a Stan interface for R that generates Stan code based on common syntax and automated data preparation. The current version of Stan uses a variation of the No-U-Turn sampler for higher performance random sampling (Betancourt, 2018). Data processing and model run were written in R version 4.0.3 (R Core Team, 2020). Models were fit after 3000 iterations (50% warm-up iterations), of four chains.

We designed different model structures i) to better capture the effects of each flood pathway, especially when reported to have occurred simultaneously, and ii) to learn about any added effects of compound inland floods, i.e., whether the final lumped loss differed from the summed average effects of individual flood pathways. Such application demands advanced features that are rarely implemented in Bayesian models, i.e., multi-memberships and monotonic effects.

Multi-membership

In a default multi-level model, each data point belongs to one group (flood pathway) only, with its own set of group-level parameters. In a multi-membership structure, however, a given data point can belong to more than one group, though each group retains its dedicated group-level parameters. During inference, the parameter used for a given data point with multiple memberships is thus a linear combination of all applicable group-level parameters (Bürkner, 2018). This model setup requires a pre-definition of weights for the multi-membership; in our model, we need to specify how each of the coinciding flood pathways contributes to the lumped loss.

Monotonic effects / Simplex

The predictor variables contamination, property-level precautionary measures (PLPMs), and flood experience are ordinal variables (Table 5.1) that might have a non-linear effect, though this must either be completely non-increasing or non-decreasing. The monotonic effect implemented in the brms package (Bürkner & Charpentier, 2020) forces this by summing the proportion of effects between each incremental category to unity in a simplex (Bürkner & Charpentier, 2020).

5.2.3 Model variants

One example of a compound loss model is FEMA: HAZUS-MH, which assumes wind and flood losses as independent and estimates the combined losses as the sum of both expected damages minus a double counting of objects that would be otherwise damaged by both hazards (see Kappes et al. (2012)). In this case. the damaging mechanisms are considered independent of each other while in a compound flood event processes (e.g., hydrostatic force and contamination of floodwaters - Kelman and Spence (2004)) readily combine. We cannot characterize each flood pathway from our data independently because the answers from our surveys represent the total or worst outcome for each variable for a given event. Hence, stepwise updates of vulnerability and damage are intractable. Thus, the coinciding flood pathways are analyzed as bulk processes.

We trained four model variants following models with two different structures (Figure 5.3). One structure uses the multi-membership feature, where compound events are assigned to multiple flood pathways. The multi-membership model structure requires weights – the proportion of each group - as input data. In the context of residential buildings, these weights are unknown. Hence, we create two model variants, assigning uniform (M_UniformW) and different weights for each membership (M_DefinedW) under the conservative assumption that the final result is a weighted averaged effect of each of the coinciding flood pathways. To be able to verify potentially added effects in the case of compound inland floods, we developed a second model structure that combines all coinciding flood-pathways into one grouping variable, obviating the need for pre-assigned weights (M_Combined); this approach is comparable to Mohor et al. (2021) but considers more groups.

We compare the three model variants above to a benchmark model (M_Baseline), which is structured as multi-membership, but admits only one flood pathway to each data point. Hence, it uses the rank of the pre-defined weights to assign each household only to the most damaging (or dominant) flood pathway reported. Table 5.3 summarizes the four model variants.

Table 5.3: Model variants

Model	Structure	Description
M_Baseline	Multi-membership	Single membership, based on the pre-defined weights order, only the dominant flood pathway reported is used
M_UniformW(eights)	Multi-membership	Multi-membership structure is given with uniform weights: all flood pathways are given the same weight and scaled to sum to unity
M_DefinedW(eights)	Multi-membership	The same structure of Model 2, but weights are pre-defined based on a simpler model fitted with flood pathways as indicator variables (in Section 5.3.1). The weights are also scaled (sum to unity)
M_Combined	Single membership	The multi-membership is lumped into individual categories for simple and compound floods

In our BMMs the likelihood function is a beta distribution (Evans et al., 2000), which is bounded between 0 and 1 and thus suitable to represent flood loss ratios (Fuchs, Heiser et al., 2019; Rözer et al., 2019). Here, the beta distribution is reparametrized to a mean μ and a precision ϕ parameter (Eq. 5.1).

$$lossratio \sim \mathrm{Beta}\left(\mu\phi, (1-\mu)\,\phi\right) \tag{5.1}$$

The mean μ is given by a linear regression with the coefficient matrix $\boldsymbol{\beta}$ with $K \times J$ elements, for K predictor variables and J data groups. The number J varies with the model structure. In model variants 1, 2, and 3, J equals the number of different pathways (J=4), while in model variant 4, J equals the number of combined categories (J=12, see Fig. 5.2). The precision parameter ϕ (Eq. 5.3) is given by a simple linear regression of water depth, the most dominant predictor variable, as noted in several modeling studies and for different flood pathways (Gerl et al., 2016; Molinari et al., 2020; Wing et al., 2020). The corresponding equations read:

$$logit(\mu_i) = \beta 0_{j[i]} + X_{i,k}\beta_{k,j[i]} \tag{5.2}$$

$$\log(\phi_i) = \alpha 0 + \alpha x_[i] \tag{5.3}$$

where subscript i refers to one of the N datapoints, subscript k refers to one of the K predictors; subscript j refers to one of the J groups; α_0 is the intercept and α is the coefficient for the precision parameter; $\mathbf{X}$ is the $N \times K$ matrix of predictor values; and $\boldsymbol{\beta}$ is the $K \times J$ coefficient matrix. For model variant 4, there is a vector of group-level coefficients for each data point i, expressed by the $j[i]$th-column of $\boldsymbol{\beta}$. For model variants 1,2, and 3, $j[i]$ is a vector of all coinciding flood pathways, and the group-level coefficient for each datapoint i is given by a weighted average with the pre-defined weights. Figure 5.3 summarizes the model variants and the data workflow.

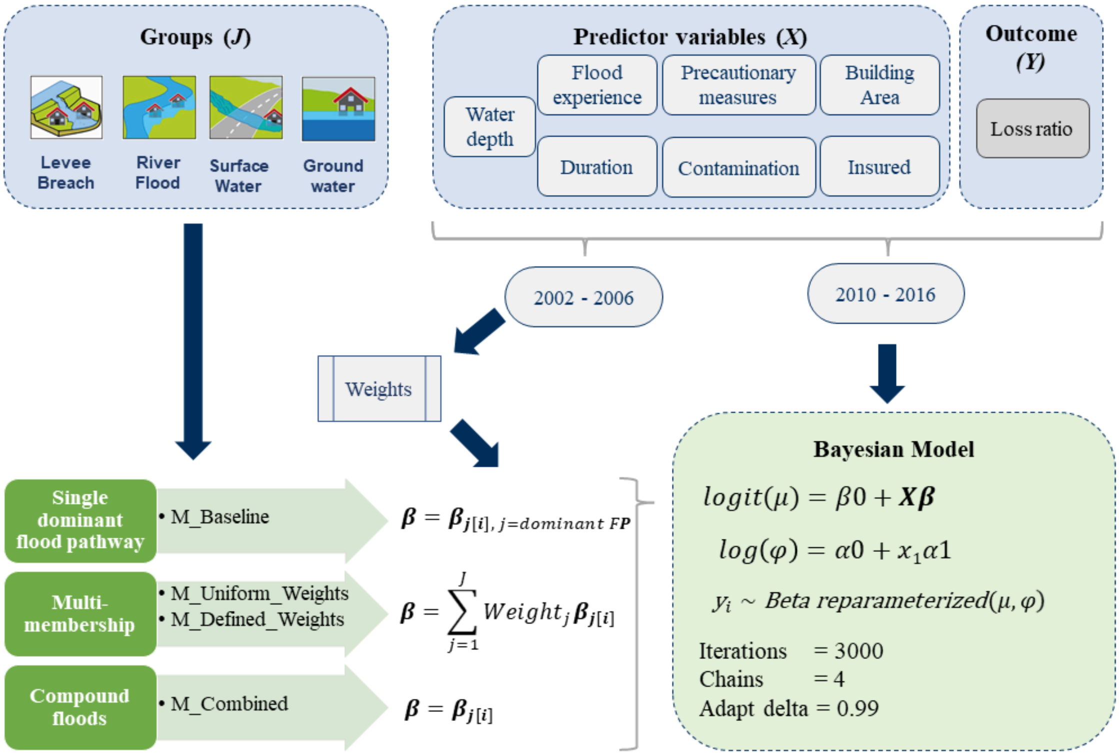


Figure 5.3: Workflow and model variants

Bayesian inference is data-driven, but explicitly includes prior knowledge. Apart from the multi-membership weights, which are fixed values, we define prior distributions for the population- and group-level parameters (Table 5.4). In the multilevel linear regression, for each predictor there is a common population-level coefficient for all datapoints, and group-level coefficients specific to each flood pathway. We use the default (non-informative) or weakly informative priors that captures previously reported positive or negative effects on flood loss, allowing for a reasonable variation. For continuous, standardized variables we used Gaussian (normal) priors, with a mean of $|0.5|$, with the sign depending on the variable, and standard deviation of 0.35, as this range allows for all reasonable parameter values (below 0.0 and above 1.0), but demagnifies extreme unreasonable values. For example, the prior for building area is set to N(-0.5, 0.35), because larger buildings generally suffer smaller relative monetary loss, all else remaining equal. One exception is the insurance indicator, as its effect has been reported ambiguously in the literature (Surminski & Thieken, 2017); hence we centered the prior for this indicator coefficient at zero and allowed for a higher variance than for other predictors.

The effects of ordered predictors modeled into monotonic effects have a magnitude and a simplex parameter. For the magnitude, we define Gaussian priors for the continuous variables. For example, the prior for the magnitude of PLPM is set to N(-0.5, 0.35), as the implementation of more flood measures, in general, reduces more losses. For the simplex, the natural prior is the Dirichlet distribution, which was set to the default Dirichlet(1), meaning all categories are equally spaced – similar to a linear effect. The precision parameter is modeled as a function of water depth, the most important controlling variable, under a weakly informative prior.

Finally, the group-level parameters are designed in brms as the product between a standard deviation (a hyperparameter individual for each predictor variable but common to all groups) over a standard normal distribution prior fitted to each group. All group-level hyperparameters have a prior of Gamma(2,5), again considering that input variables are standardized, and this variation is suitable for avoiding extreme values, which could hinder model conversion, but allows for all probable ranges.

Table 5.4: Priors of model parameters

Model parameter	Prior
For the population-level parameters	
Intercept	N (+0.0, 1.00)
Water depth	N (+0.5, 0.35)
Building area	N (-0.5, 0.35)
Contamination	N (+0.5, 0.35)
Duration	N (+0.5, 0.35)
PLPMs	N (-0.5, 0.35)
Insured	N (+0.0, 0.50)
Flood experience	N (-0.5, 0.35)
For the group-level parameters	
SD	Gamma (2.0, 5.0)
For the precision parameter	
phi_WaterDepth	Gamma (-2.0, 0.1)

5.2.4 Analyses

The first step after running the models is to evaluate the convergence of the chains by visual inspection of the posterior distributions of model parameters, visual inspection of the posterior predictive distribution of the outcome (loss ratio), and the use of indexes. Commonly used indexes are Gelman-Rubin score (R-hat) (Kruschke, 2015) and the effective sample size ratios (N_eff ratio) (McElreath, 2020).

We use the term credible for the most likely parameter estimates based on the 90% highest density interval (HDI). Similarly, focusing on the model variant M_Combined, we compare the loss ratio estimates for compound flood cases and single flood pathway cases to assess whether there is an added effect for compound floods. We deem an effect credible if the estimate of a compound case is credibly higher than the average of estimates of respective single flood pathway cases.

To allow model comparison, we used pointwise scores of predictive accuracy based on information criteria (Piironen & Vehtari, 2017). The comparison of model performances is based on the expected log pointwise predictive density (elpd_loo) (Vehtari et al., 2017), and the Bayesian version of the coefficient of determination R^2 for the prediction of the training dataset and the test dataset. The Bayesian R^2 is an adaptation considering the posterior predictive distribution, instead of a central value, and likewise returns a distribution of values for each simulation (Gelman et al., 2019).

In Bayesian or statistical modeling, there are often multiple model candidates with little or no difference that would justify the exclusion of one and the adoption of another model (Gelman et al., 2019; Piironen & Vehtari, 2017). Instead, the combination of candidate models, even when the "true" model is not known or not achievable, is a natural outcome (Beven, 2006; Yao et al., 2018). Under the Bayesian approach, the simpler way of doing that is stacking and model averaging. Bayesian model averaging (BMA) is a weighted average where the weights are estimated by their posterior probability (based on the elpd), which in turn depends on the marginal likelihood, but also the priors (Yao et al., 2018). Stacking, on the other hand, averages point estimates based on PSIS-LOO (Pareto-smoothed importance sampling, an efficient and robust estimation of the otherwise too burdensome LOO cross-validation (Vehtari et al., 2017)) and minimizing the Leave-One-Out (LOO) error (Yao et al., 2018). Although both approaches generate some form of weighted average across models, stacking is recommended as more proximate to a Bayesian solution (Yao et al., 2018), and especially when the model candidates are not carefully chosen or when the "true" model is not among the model candidates (McElreath, 2020). We employ both methods to observe the congruence of the model weights.

5.3 Results

5.3.1 Multi-membership weights definition

To estimate the weights of each flood pathway we trained a single-level model with the test data (Fig. 5.3). This Bayesian model has the same predictors as the other model variants, without priors and having each flood pathway membership as indicator variables to estimate the average loss ratio from different pathways. For the sake of simplicity, the coefficients are taken as the rescaled mean linear predictors (Table 5.5). For example, for a resident who reported levee breaches, river flood, and groundwater flood, the uniform weights would be 1/3 for each pathway, whereas the weights based on the auxiliary model would be 0.399, 0.319, and 0.282, respectively, and the dominant flood would be levee breach (assigning a unity weight to levee breaches and zero weight to other pathways).

Table 5.5: Multiple pathways weights training

	pGroundwater	pSurface	pRiver	pLevee
Ratio to the smallest coefficient	1.000	1.050	1.132	1.415
Scaled coefficient (sum=1.0)	0.218	0.228	0.246	0.308

5.3.2 Model variants diagnostics

After estimating the weights for multiple pathways, we fitted the four model variants with the training data set. Table 5.6 shows that the R-hat value and N_eff ratio of each model variant indicate converged and well-mixed chains, so that the simulated posterior distributions are reliable.

Table 5.6: Model variants convergence indicators

Model variant	max R-hat	min N_eff ratio
M_Baseline	1.004	0.240
M_UniformW	1.003	0.234
M_DefinedW	1.004	0.261
M_Combined	1.002	0.268

A visual inspection of the goodness-of-fit of the posterior predictive distribution indicates that the models are sufficiently stable and representative of the data generating process (Figure 5.4). Visual inspection of the chains revealed no excessive autocorrelation or multi-modal distribution.

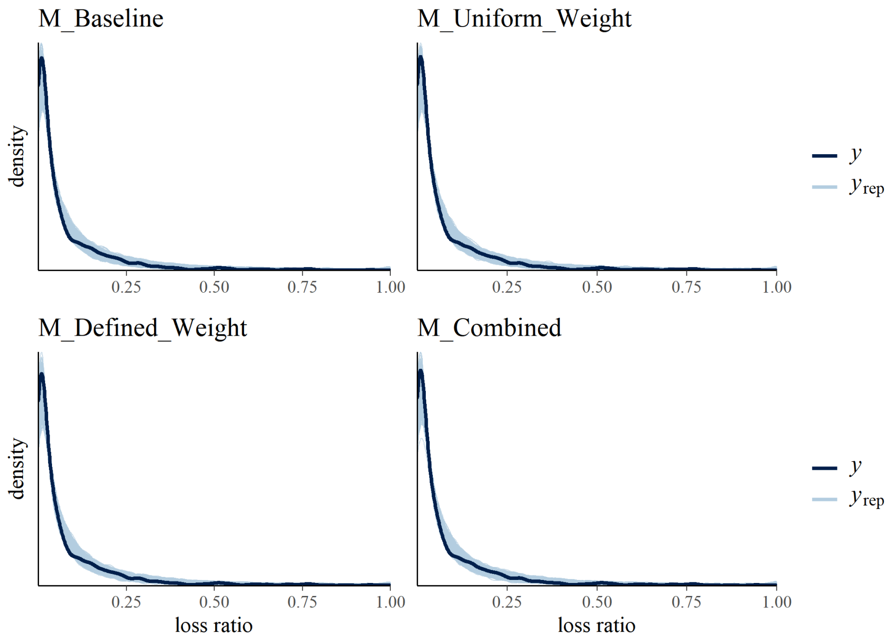


Figure 5.4: Posterior predictive distribution of model variants (light blue lines, yrep) compared to observed distribution (dark line, y) of the loss ratio

5.3.3 Model variants parameters

Figure 5.5 shows the 90% highest density interval (HDI) summed population- and group-level effects of each flood pathway and model variant. Most coefficient estimates are credibly different from zero across all model variants and most of the flood pathways (Figure 5.5). In few cases, flood experience had only credibly negative effects for river floods and levee breaches, whereas PLPMs were not credible for levee breaches. We highlight that the coefficients for insurance are all credibly positive, despite the zero-centered prior. In analyzing insurance purchase and risk reduction in Germany, both Hudson et al. (2017) and Osberghaus (2017) could not observe the effects of moral hazard in insurance purchasers, when the insured population show more risk-averse behavior or make them more vulnerable. But rather, Hudson et al. (2017) identified adverse risk selection, where those most at risk are the ones purchasing insurance, which could reflect the in average higher loss for the insured population.

All model variants have large overlaps between the coefficients across flood pathways (Figure 5.5). When comparing the coefficients across flood pathways of the same model, there are several credibly different coefficients for the intercept and the water depth, but only in a few cases for the building area (at model variant Baseline), ‘contamination’ (at model variants M_UniformW, M_DefinedW, and M_Combined), ‘flood experience’ (at model variants M_Baseline, M_UniformW, and M_DefinedW), and ‘insured’ (at model variant M_Baseline). No credible differences were found for ‘PLPMs’ or ‘duration’. We find that, for all model variants, the effect of water depth on surface water floods is credibly

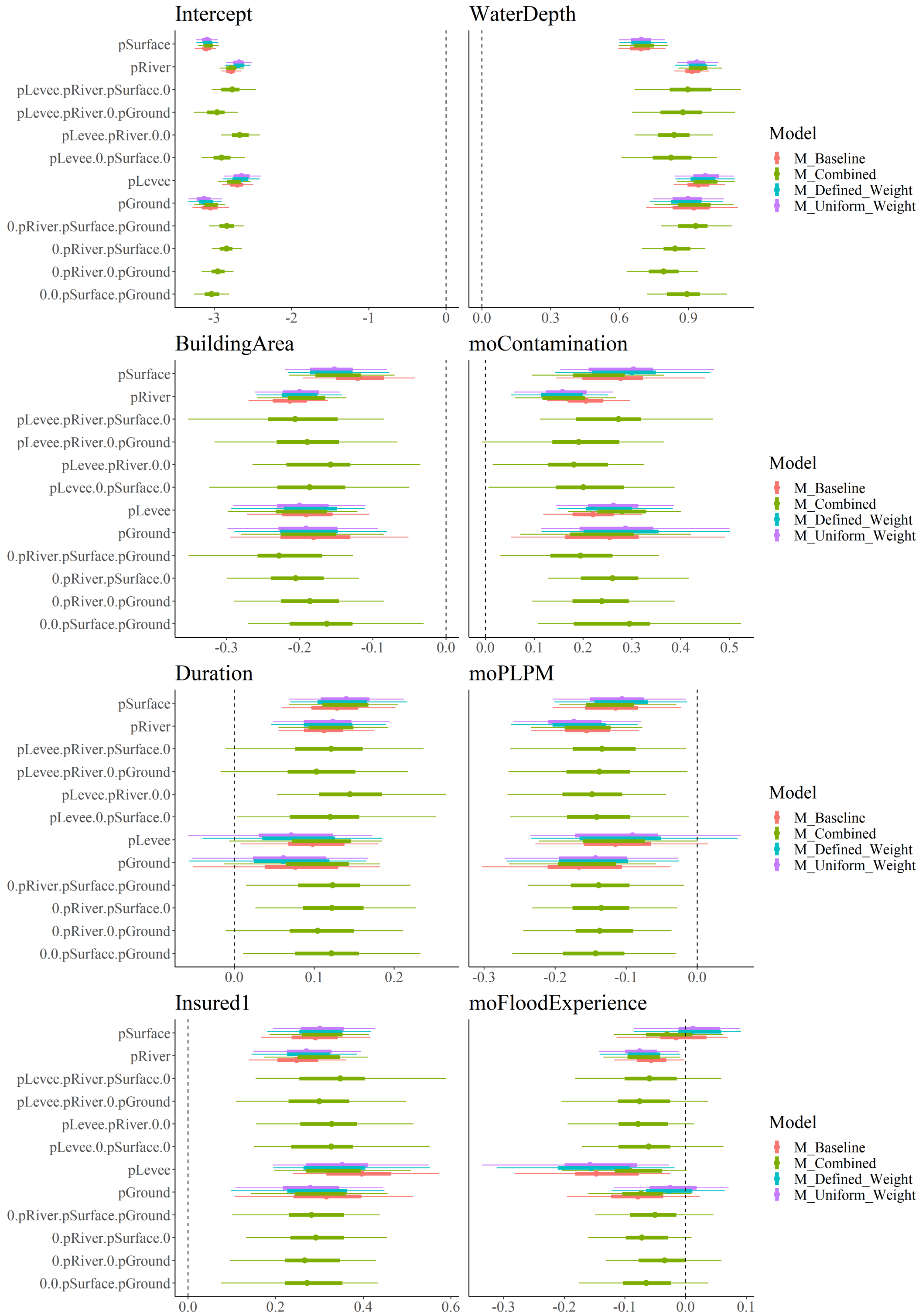


Figure 5.5: Summed population and group-level effects for each flood pathway and model variant. The model variants M_Baseline, M_UniformW, and M_DefinedW only have coefficients for single flood pathways. Models are based on data from 2010 to 2016. Thick lines show the 50% HDI, thin lines, the 90% HDI

smaller than for any other (single) flood pathways. In the multi-membership models (M_UniformW, and M_DefinedW), (more recent) flood experience leads to a credibly larger loss-reducing effect on levee breach floods than on surface water or groundwater floods. The credible differences of the intercept indicate differences in the average loss ratio across flood pathways for average predictor values. However, this should not be examined in isolation from other coefficients. A comparison of final loss estimates is presented in section 5.4.5 for M_Combined specifically for the compound cases, compared to its composing single flood pathways. Less than a fourth of all flood pathway pairs had credible different coefficients (see Table C.1). Table 5.7 show selected credibly different pairs of coefficients of water depth and flood experience only, along with the posterior medians of the distribution of differences and the fraction of each distribution above zero.

When comparing estimates across model variants, only the coefficients for single flood pathways can be compared for each predictor variable. We found no credible differences for a 90% probability. In comparing the standard deviation of the coefficient posterior estimates (of single flood pathways only) across models we note an average increase of 5% between the multi-membership models (M_UniformW and M_DefinedW) and M_Baseline (median +5%, range between -22% (Water Depth, Ground) and +35% (Duration, Levee)). The two multi-membership models showed on average no difference (0%; range between -6% and +5%). The standard deviations of coefficients of M_Combined are on average 6% smaller than the two multi-membership models (median -6%, range between -33% (Flood Experience, Levee) and +11% (Water Depth, Ground)).

5.3.4 Model performance and comparison

Figure 5.4 showed that all model variants were able to reproduce the data generation process for the training data. When predicting the loss ratio for flood events for the test data, the model captures the distribution of observed loss ratios (Figure 5.6).

Table 5.8 shows the elpd_loo and the Bayesian R^2 of all model variants. The differences in elpd_loo across model variants (in reference to the M_UniformW model variant that has the largest elpd_loo) are low, suggesting no or very little gains, especially when comparing the difference in their standard errors (Vehtari, 2020).

Table 5.9 shows the weights estimated through modified methods of stacking and BMA (Pseudo-BMA uses Akaike's information criterion for weighting) implemented in the LOO package based on Yao et al. (2018). The different methods agree on the highest weight being given to the M_UniformW model and the lowest weight to the M_Combined model variant. This ranking agrees with the predictive performance in Table 5.8, and reflects how frequent each model outperforms others (Gelman et al., 2020). Still, these different model variants may be useful when complementing each other.

Table 5.7: Selected pairs of coefficients with 90% credible differences for water depth and flood experience predictors (from Figure 5.5)

Model variant	Variable	Difference in flood pathways estimates	Median of difference	Fraction of distribution beyond zero
Baseline	WaterDepth	pLevee - pSurface	0.25	>99.5%
Baseline	WaterDepth	pRiver - pSurface	0.22	>99.5%
Baseline	WaterDepth	pSurface - pGround	-0.23	4%
UniformW	WaterDepth	pLevee - pSurface	0.28	>99.5%
UniformW	WaterDepth	pRiver - pSurface	0.24	>99.5%
UniformW	WaterDepth	pSurface - pGround	-0.20	3%
DefinedW	WaterDepth	pLevee - pSurface	0.27	>99.5%
DefinedW	WaterDepth	pRiver - pSurface	0.24	>99.5%
DefinedW	WaterDepth	pSurface - pGround	-0.20	4%
Combined	WaterDepth	pLevee.0.0.0 - 0.0.pSurface.0	0.28	>99.5%
Combined	WaterDepth	pLevee.0.0.0 - 0.pRiver.pSurface.0	0.14	90%
Combined	WaterDepth	pLevee.0.0.0 - 0.pRiver.0.pGround	0.19	95%
Combined	WaterDepth	0.pRiver.0.0 - 0.0.pSurface.0	0.25	>99.5%
Combined	WaterDepth	0.pRiver.0.0 - 0.pRiver.0.pGround	0.16	94%
Combined	WaterDepth	0.0.pSurface.0 - 0.pRiver.pSurface.0	-0.14	7%
Combined	WaterDepth	0.0.pSurface.0 - pLevee.pRiver.pSurface.0	-0.19	8%
Combined	WaterDepth	0.0.pSurface.0 - 0.0.0.pGround	-0.22	3%
Combined	WaterDepth	0.0.pSurface.0 - 0.0.pSurface.pGround	-0.19	5%
Combined	WaterDepth	0.0.pSurface.0 - 0.pRiver.pSurface.pGround	-0.23	1%
Baseline	Flood Experience	pLevee - pSurface	-0.13	7%
UniformW	Flood Experience	pLevee - pSurface	-0.17	4%
UniformW	Flood Experience	pLevee - pGround	-0.13	8%
DefinedW	Flood Experience	pLevee - pSurface	-0.17	6%
DefinedW	Flood Experience	pLevee - pGround	-0.13	9%

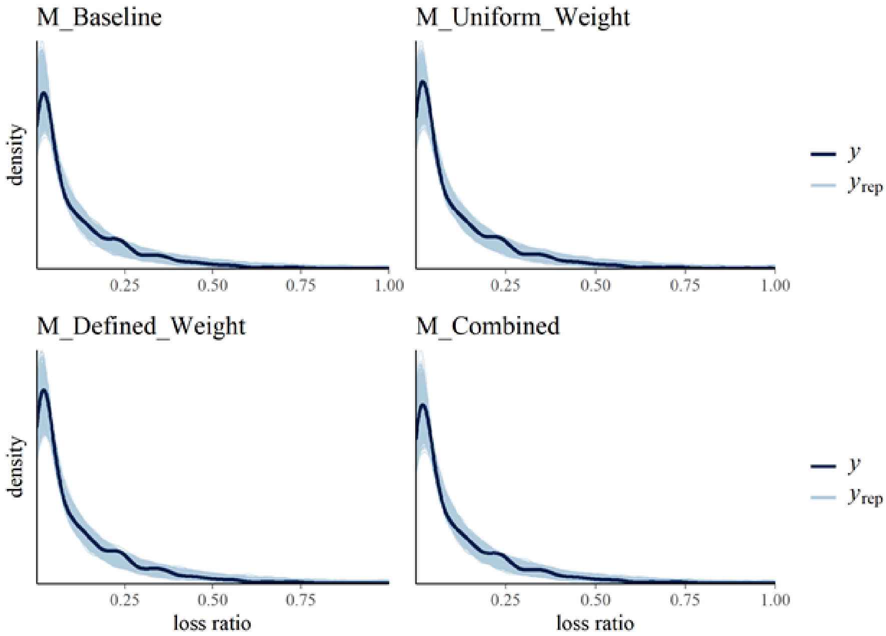


Figure 5.6: Posterior predictive distribution of loss ratio (yrep) with the test data set (2002-2006), compared to the observed distribution (y)

5.3.5 Effects added by compound floods

We used the M_Combined model variant to assess whether the final lumped loss from multiple flood pathways is more than their average.

For a direct comparison of estimates, we draw posterior predictive estimates based on fixed predictor values, varying only the combined flood pathways. We set five scenarios that capture the range of predictor values and rank them in terms of expected flood loss. The values are based on the range of ordinal variables or the standard deviation of metric variables, ordered according to the predictor weights from the combined model.

Table 5.8: Model variants predictive performance

Model variant	Bayes_R2 with the training dataset median (90%)	Bayes_R2 with the test dataset median (90%)	elpd_loo	Difference of elpd_loo	Standard error of the difference
M_Baseline	0.450 (0.41-0.48)	0.478 (0.43-0.51)	2975	-0.08	0.35
M_UniformW	0.459 (0.41-0.50)	0.460 (0.41-0.50)	2977	-	-
M_DefinedW	0.457 (0.42-0.49)	0.462 (0.41-0.50)	2977	-1.84	3.47
M_Combined	0.461 (0.42-0.49)	0.436 (0.37-0.49)	2972	-5.20	3.32

Table 5.9: Model weights for different Bayesian model combination methods

Model variant	Stacking of predictive distribution	Pseudo-BMA + weighting
M_Baseline	0.391	0.248
M_UniformW	0.553	0.391
M_DefinedW	0.055	0.324
M_Combined	0.000	0.037

For example, larger values of water depth or lower values of flood experience predict higher losses (Table 5.10).

Table 5.10: Scenarios of flood loss for the comparison of flood pathway combinations. Numbers are standard deviations or ordinal values of the input data

	HIGHEST	HIGH	MODERATE	LOW	LOWEST
Water Depth	2	1	0	-1	-2
Building Area	-2	-1	0	1	2
Duration	2	1	0	-1	-2
Contamination	2	2	1	0	0
PLPMs	0	0	1	2	2
Flood Experience	0	1	2	3	4
Insured	1	1	0	0	0

The predictive posterior distribution is summarized in Figure 5.7, ordered by the median estimates of the highest flood-loss scenario. The posterior predictive distribution of the loss ratios for groundwater floods using M_Combined is slightly higher than that for surface water floods, although the weights developed in section 5.3.1 show the contrary, at least regarding central estimates.

With the loss ratio estimates for each flood pathway combination, we compare the distributions as the proportion of the flood-loss estimate of a compound flood (e.g. river and surface water floods) to the average of independent estimates for each single flood pathway (Eq. 5.4).

$$proportion = \frac{\text{loss ratio estimate of compound case(pRiver AND pSurface)}}{\text{average of estimates(pRiver,pSurface)}} \tag{5.4}$$

We consider an effect credibly higher when 90% of the posterior distribution is above unity (Table 5.11). We find that none of the cases considered showed credibly that compound flood-loss estimates are larger than the average of their composing single flood pathways.

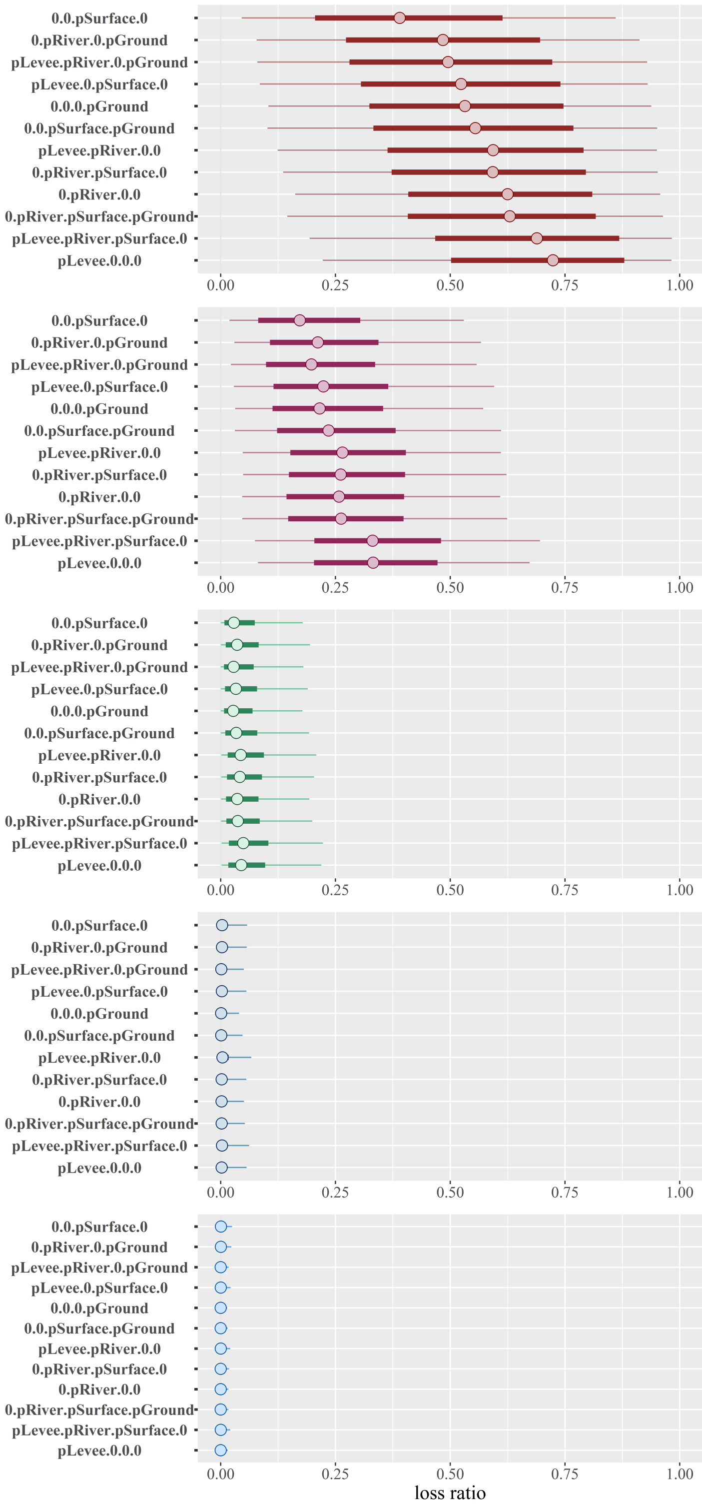


Figure 5.7: Posterior predictive distribution loss ratio under five flood-loss scenarios (a-e) with M_Combined. Thick lines show the 50% HDI, thin lines, the 90% HDI

Likewise, these relationships also show no credible added effect of compound cases under the other flood-loss scenarios (Table 5.12); largely reflecting lower weights (Figure 5.7).

Table 5.11: Comparison of estimates of compound cases to the average of single flood pathways in the highest loss scenario. Lower and upper bounds represent the 50% HDI interval

Compound inland flood case	Mode	Lower-bound HDI	Upper-bound HDI	Fraction of distribution beyond unity
pLevee and pRiver	1.06	0.71	1.48	0.44
pLevee and pSurface	1.15	0.70	1.69	0.48
pRiver and pSurface	1.32	0.87	1.93	0.60
pLevee and pRiver and pSurface	1.34	0.98	1.78	0.66
pRiver and pGround	1.09	0.63	1.58	0.40
pLevee and pRiver and pGround	1.14	0.68	1.58	0.39
pSurface and pGround	1.30	0.78	1.90	0.61
pRiver and pSurface and pGround	1.34	0.93	1.88	0.61

5.4 Discussion

We explored various model structures with single and multiple flood pathways to assess how much these models might improve predictions of flood-loss ratios. The data we used is amenable to multilevel, multi-membership models that consider different flood pathways, as previously shown by Mohor et al. (2021). However, such implementation did not improve loss estimation. Final estimates intrinsically incorporate the uncertainty of each predictors' effect as well as the uncertainty in the identification of flood pathways. We discuss below the lessons from the loss ratio estimates, the limitations of the data, our model choices, and alternatives to characterize the predictor weights on financial loss of different flood pathways and under compound inland floods.

5.4.1 Discussion of the results / Uncertainty in posterior loss estimates

All our model variants are able to replicate the observations, as seen in the posterior predictive distributions (Figure 5.4 and Figure 5.6). Adding the compound inland flood cases changed little from the baseline model (M_Baseline) that considers the dominant flood pathways only. The multi-membership model variants (M_UniformW and M_-DefinedW) learned coefficients are not credibly different from the baseline model. Regression coefficients differ credibly across some flood pathways within each model (Table 5.7), but each coefficient overlaps across models. The changes in coefficients' dispersion had little effect on the overall predictive outcomes. Acknowledging coinciding flood pathways confirmed previous reports of predictor variables having different effects for different flood

Table 5.12: Comparison of estimates of compound cases to the average of single flood pathways under each conditional scenario

Conditional scenario	HIGHEST		HIGH		MODERATE		LOW		LOWEST	
Compound inland flood case	Mode	Fraction beyond unity	Mode	Fraction beyond unity	Mode	Fraction beyond unity	Mode	Fraction beyond unity	Mode	Fraction beyond unity
pLevee and pRiver	1.06	0.44	0.99	0.42	1.31	0.45	1.16	0.45	1.28	0.46
pLevee and pSurface	1.15	0.48	1.05	0.43	0.73	0.41	1.13	0.40	0.96	0.39
pRiver and pSurface	1.32	0.60	1.21	0.56	0.92	0.48	0.77	0.39	1.06	0.37
pLevee and pRiver and pSurface	1.34	0.66	1.43	0.61	1.11	0.48	0.96	0.38	1.08	0.35
pRiver and pGround	1.09	0.40	1.02	0.43	1.22	0.47	1.29	0.47	1.61	0.49
pLevee and pRiver and pGround	1.14	0.39	1.02	0.35	0.94	0.35	0.81	0.34	0.94	0.33
pSurface and pGround	1.30	0.61	1.38	0.54	1.23	0.46	0.86	0.36	0.56	0.32
pRiver and pSurface and pGround	1.34	0.61	1.43	0.54	1.41	0.45	1.17	0.36	0.52	0.29

pathways. However, in terms of loss-ratio estimation, the performance of the model is equivalent to that of a model with only dominant flood pathways.

The uncertainty in our loss ratio estimates with explicit combined categories (M_-Combined) is tied to substantial overlap of coefficients for different flood pathways and compound cases. Hence, the added effect of compound cases appears to be minute. The models' convergence diagnostics showed no systematic problem, and in most cases, despite some uncertainty, predictor coefficients showed credible effects (positive or negative signals). Therefore, we do not expect the model fitting to be the cause of uncertainty, but rather the representation of the predictor variables and the data at hand. Before such effects can be ascertained, the uncertainty in model parameters, must, however, be reduced. Nonetheless, central estimates of the posterior distributions point towards larger financial loss ratios under compound events compared to the estimates from each single flood pathway, as shown by the modes of the posterior distribution of proportions (Table 5.11).

To better assess the performance of our models, we would like to compare results with other object-level probabilistic flood loss models. This task, however, is not straightforward. If predictors are not the same, a model harmonization and a form of reduction to common predictors is required, which consequently makes especially multi-variable, probabilistic models lose explanatory power (Gerl et al., 2016). As the comparison with external models was not in our focus, we searched for similar probabilistic flood loss models that precluded model harmonization. Most flood loss models are deterministic (Gerl et al., 2016), though from different approaches, such as stage-damage functions (Huizinga et al., 2017), rule-based models (Thieken et al., 2008), or regression trees (Merz et al., 2013). There are only a few probabilistic flood loss models for residential buildings at the object level available in the literature. de Risi et al. (2013) employed a probabilistic approach, but calculated the collapse probability, rather than partial damages. Nofal and van de Lindt (2020) estimated damage states (ordinal response) only. Vogel et al. (2018) discussed the methodology and training of Bayesian networks (BNs) for the relative financial losses without presenting final loss estimates. Wagenaar et al. (2017) presents only absolute losses. Lüdtke et al. (2019) presented aggregated losses only. These different model outcomes preclude a direct comparison with our results. Dottori et al. (2016) present a component-by-component multivariate synthetic model with probabilistic results. Yet some of their damage functions are estimated probabilistically, while other functions of the model are deterministic, and that the model uses an expert-based approach rather than a data-driven approach. Moreover, their results combine both structural and non-structural damage. Rözer et al. (2019) presented a Gaussian regression, a Beta regression, and a Random Forest model, using a subset of our dataset specifically towards pluvial floods, but using different predictors. The authors present the results to a single non-specified case with a loss magnitude similar to our "low" flood-loss scenario (Figure 5.7[d]). In Rözer et al. (2019) results of the Beta model achieved a similar 90% HDI width to ours in the respective scenario, but our scenarios of higher flood-loss led to higher HDI widths. Rözer et al. (2019) found sharper estimates using Random Forest for this case but concluded that, in aggregated results, the Beta regression model performed better than the Random Forest model. Schröter et al. (2014) implemented BNs and present loss estimates, but to unspecified scenarios, thus we cannot match their scenarios with ours for a direct comparison. They show that the BNs quantile ranges (QR90) are larger than the deterministic models (considering the uncertainty in input data). Their QR90s range is similar to our models' QR90 for the "highest" flood-loss scenario (Figure 5.7a), while for lower flood-loss scenarios the QR90 shows unrepresentative values due to the division with very low values.

5.4.2 Discussion of the data / Insights from modeling compound cases

Our dataset comprised all 15 combinations of the four flood pathways, including combinations that have been reported in previous flood events and unlikely ones, which were removed from our analyses (Fig. 2). The latter ones were also less frequent, reflecting the uncertainty in pathway recognition, but showing no (large) systematic biases. Macdonald et al. (2012) emphasized the difficulty of comprehensive data collection on flood pathways and their combinations. They also relied on observation from residents to know which houses were affected by groundwater and river floods, notwithstanding an existing, but insufficient monitoring network.

Besides the flood pathway identification, the model structures implemented (M_UniformW and M_DefinedW) require weights to the coinciding flood pathways. However, discerning the contribution of losses from different hazards is an underdeveloped task. For hurricanes, attributing the damage to either wind or flood forces has been achieved by assigning the damages to the different physical hazards (Baradaranshoraka et al., 2017; Li et al., 2012). This task is more challenging and may require a more complex model setup for compound (inland) floods, where different flood mechanisms can occur in combination or in sequence. Our predictor variables, especially the variables that describe the hazard characteristics, are bundled, i.e., we cannot distinguish the contamination level or water depth, for example, from each coinciding flood pathway source.

There have been recent attempts to split the hazard after hurricanes/cyclones when storm surges (coastal floods) and fluvial floods occur at the same time and place, at least regarding their effect on the maximum water level (Gori et al., 2020; Huang et al., 2021). These developments still find difficulty in estimating the proportion of each flood source, as inundation effects are non-linear and spatially (topographic) dependent. The hydraulic modeling of flood inundation could help identify and distinguish effects of different flood pathways. Yet such modelling of surface water floods and groundwater floods is less developed than that of river and coastal floods (Macdonald et al., 2008; Rosenzweig et al., 2021), despite developments for the modeling of urban floods (Bulti & Abebe, 2020) and groundwater floods (Collins et al., 2020). Part of the bottleneck for such developments is the lack of measurements that systematically record data to train and validate such models (Macdonald et al., 2012; Neal et al., 2012; Rosenzweig et al., 2021), opposed to the numerous tidal gages and river gauges used in coastal and river flood modeling. For example, Chen et al. (2010) and Apel et al. (2016) modeled a compound surface water and river flood, without validation of the former flood pathway due to lack of observed data.

If loss models of compound inland floods are to be informed by hydraulic models, that should be achieved with a single model that takes into account all flooding mechanisms, for the simple summation of individual mechanisms leads to great biases (Chen et al., 2010; Huang et al., 2021). Despite the recently increasing number of such studies, they are still very localized, data and resource intensive, and not always validated. The improvement of these models for a single flood pathway is required before learning more complex models able to characterize their combined impact and consequentially distinguish each flood pathway's contribution to the final flood magnitude and impact.

5.4.3 Discussion of the model choices

As in most modeling problems, a trade-off between bias and variance is sought when selecting the predictor variables. We used the same predictor variables proposed by Mohor et al. (2021) and sought to improve the representation of ordered variables using the monotonic effect and using the water depth as a predictor for the Beta distribution precision parameter. Compared to the model of Mohor et al. (2021), added monotonic effects lead previously ambiguous coefficients to being credible, especially those for groundwater floods. Yet, little was achieved in reducing the spread of model parameters and final loss estimates.

Previous depth-damage models have been developed with multiple non-linear shapes (Jongman et al., 2012; Molinari et al., 2020). Similarly, works like the one from Maiwald et al. (2021) show that there are multiple ways of representing floodwater velocity in a model, including non-linear and interaction effects with the water depth, some with better performance than others. In that direction, non-linear responses, data transformations, and interacting effects may improve both hazard and loss models. This leads to numerous model candidates and such extensive exploration, without an underlying reason for which interaction is physically or conceptually preferred, is however prohibitive.

5.5 Conclusions

The modeling of financial flood losses considering the coincidence of different flood pathways requires advanced techniques such as Bayesian multilevel models (BMMs), which discern model parameters for different groups (i.e., single pathways or combination of pathways) in the data. On the one hand, admitting multiple memberships may reveal in more detail the effects that lead to the final loss estimate. This application requires, however, the prior definition of the relative contribution of each coinciding flood pathway, which we set as uniform or defined based on a simpler model. The definition of weights based on a single-level linear model returned estimates close to the uniform (non-informed) weights set. On the other hand, the multi-membership model variant is unable to capture a potentially added effect due to the coincidence of different flood pathways simultaneously without a pre-defined set of weights. We are unaware of other studies that addressed such challenges for compound inland floods. We thus trained a different model variant where compound cases were explicit to the model, allowing for such a signal to be learned. Comparing loss ratio estimates of compound cases with estimates from the individual flood pathways showed no credible difference, when the distribution of ratios is analyzed, although they were mostly above unity. We infer that the general uncertainty in loss estimates masks the added effect of compound inland floods.

To better capture the proportional effect of each flood pathway for a given compound event, complex hydraulic models that integrate all mechanisms might reveal further insight. Distinguishing, at least to some extent, the characteristics of each coinciding flood pathways in inland floods (e.g. share of the water depth, the share of water contamination, etc.) could help to define weights between flood pathways under compound inland floods. The improvement of hazard (e.g., hydraulic) models for single flood pathways is still necessary to inform the partial contribution of each coinciding flood pathway to a loss model. The contribution of each flood pathway in compound costal-river floods has been studied and it is a highly non-linear relationship that depends on local topography (Gori et al., 2020; Huang et al., 2021) and is currently available only for few selected locations. New studies might indicate a general trend that could in turn inform the financial loss model.

The identification of an added effect of compound events suffered from the uncertainty of loss estimates. Central estimates point towards an added effect (i.e., compound events are more damaging than the averaged effect of individual flood pathways), but the variance of the loss estimates hardly highlights any credible effect. Aleatoric uncertainty will remain, as there is a natural variability of the damage. Yet, epistemic uncertainty might be reduced with a better representation of the damaging process per pathway.

Flood pathway identification and classification must be clarified and validated, as floods are still defined diversely in the literature. At times, flood events are distinguished by their generating process (Merz & Blöschl, 2003), at times by flood type (i.e., fluvial, pluvial, coastal), resulting in non-uniform and ambiguous categories. For example, “urban floods” may refer to the overflow of riverbanks that runs through an urban environment (Neal et al., 2009), or to the waters released by overpowered drainage systems (Rosenzweig et al., 2021). Yet, there has been no robust classification, let alone predictive loss modelling, of floods. Hence, we advocate that flood pathways, rather than drivers, should be distinguished for the purpose of loss modeling, and did so in our model structure by classifying the household’s immediate observations into equivalent flood pathways (Tab. 5.2).

Current efforts to identify coinciding flood pathways and employ complex models hardly improved loss estimation, and the adoption of a dominant flood pathway performs equally well. One way forward is the gathering of data that distinguishes coinciding flood pathways or the use of hazard models as proxy. Alternatively, interaction terms or non-linear data transformations, if already tested or conceptually proven, should be incorporated in the loss model, reducing uncertainties in the model parameters and consequently in the loss estimates, clarifying the role of coinciding flood pathways.

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Chapter 6

Synthesis and Conclusion

6.1 Synthesis

The classification of floods is mostly based on an event's generating conditions, commonly termed fluvial, pluvial, and coastal floods, or even further as suggested by Hundecha et al. (2020) and Merz and Blöschl (2003). These classifications focus on the event's meteorological and hydrological features, neglecting damaging processes. Furthermore, most loss models have addressed only one flood type at a time (Gerl et al., 2016), but have performed poorly when transferred to different settings (Figueiredo et al., 2018; Jongman et al., 2012; Schröter et al., 2014). Conversely, flood pathways, based on the Source-Pathway-Receptor framework (Hall et al., 2003; Sayers et al., 2002), focus on the flood waters at the object-level in order to better reflect the damaging processes and act as a predictor of financial losses.

Having identified these shortcomings of flood loss modelling, this thesis has aimed to improve financial loss model transferability by integrating (multiple) flood pathways into the same model. Before doing this, it was necessary to perform comprehensive data analysis to better understand the role flood types and pathways play in damage in the residential sector.

The previous chapters examined and answered the following research questions:

1. In which aspects do flood pathways of the same (compound inland) flood event differ?

In chapter 2, I showed that warning systems' performances, emergency, and adaptation measures mostly reflect general flood type, but characteristics of the hazard at the object level and with respect to (financial) impacts and recovery are dominated by the flood pathways.

2. How much do factors which contribute to the overall flood loss in a building differ in various settings, specifically across different flood pathways?

In chapter 3, I showed that most aspects of the flood addressed in the dataset are statistically different across the studied flood pathways. Furthermore, I demonstrated which factors available in the dataset are most relevant to loss ratio modelling; these factors include characteristics of the hazard, of the affected building, and indicators of preparedness (see Table 6.1).

3. How well can Bayesian loss models learn from different settings?

In chapter 4, I showed that Bayesian multilevel models (BMMs) can learn different settings simultaneously, but nonetheless differentiate between each setting. Structuring data across different years or regions is hardly informative. However, distinguishing across flood pathways is very informative for loss modelling.

4. Do compound, that is, coinciding flood pathways result in higher losses than a single pathway, and what does the outcome imply for future loss modelling?

In chapter 5, I showed that BMMs can also differentiate model parameters for each flood pathway in compound floods, but the detail of currently available data is not precise enough to learn the synergistic effects of compound inland floods on financial losses.

In this chapter, the above statements are first explained in detail. This is followed by a general discussion in the following sections.

6.2 Main Findings

This exploration is data-driven, supported by a large, multifaceted database (Kellermann et al. (2020) and extensions thereafter) that goes beyond the commonly used predictors (such as water depth; Gerl et al., 2016; Wing et al., 2020). The database comprises a total of 6000 datapoints regarding flood-affected households in eight large flooding events in Germany, which affected 14 of the 16 German Federal States. Not all datapoints have valid loss ratios. Chapter 2 analyses all aspects of these data statistically but does not include a model, while chapters 3, 4, and 5 present at least one model each. The models' basic features and the predictor variables are summarized in Table 6.1. Because two model types, one being deterministic (OLS) and the other being probabilistic (BMM) were developed, two variable selection procedures were accomplished.

Table 6.1: Regression predictor variables

	Chapter 3	Chapter 4	Chapter 5
Model type	Ordinary least squares (OLS)	Bayesian multilevel model (BMM)	
Grouping variable	None OR Dominant flood pathway	Flood pathway OR Region OR Event	Compound flood pathway OR Flood pathway
Predictor variables			
Hazard characteristics	Water depth	Water depth	Water depth
	Contamination	Contamination	Contamination
	Duration	Duration	Duration
	Velocity		
	Flood pathway [as indicator]		
Building characteristics	Building area	Building area	Building area
	Building quality		
	Cellar		
Preparedness	Property-level precautionary measures (PLPMs)	PLPMs	PLPMs
	Emergency measures		
	Insurance	Insurance	Insurance
	Efficacy of PLPMs		
	Flood experience		

6.2.1 In which aspects do flood pathways of the same (compound inland) flood event differ?

Although using a slightly different attribution of flood pathways than in other chapters, the detailed analysis of the 2013 and 2016 events in chapter 2 demonstrates that warning systems' performance and coping options (i.e. adaptation measures) are primarily dominated by the general flood type. However, hazard characteristics at the object level, (financial) impacts, and recovery also differ in respect of the flood pathways of a single flood event. This supports the inclusion of flood pathways and related information in risk communication so that those who receive flood warnings are better prepared for specific types of life-threatening and destructive flood pathways. Moreover, further differentiation of flood types into flood pathways is also recommended for loss modelling, since both hazard characteristics and impacts are significantly different at the object level; this differentiation could improve loss estimation.

6.2.2 How much do factors which contribute to the overall flood loss in a building differ in various settings, specifically across different flood pathways?

Through univariate assessments, I compared the reported raw values of each of the 29 predictor candidates across flood pathways (i.e. levee breaches, river floods, surface water floods, and groundwater floods) using a statistical approach. Except for socioeconomic features, all other aspects of the flood event (i.e. hazard characteristics, characteristics of the affected residential buildings, early warning, and indicators of preparedness; see again Table 1.2) are statistically different across flood pathways. Early warning and preparedness indicators seem to reflect the ability to forecast upcoming events and create general risk maps. Relatedly, insurance coverage may also be linked to risk perception and mapping. Such differences drive the incorporation of flood pathways into loss models, although these differences may not always have an effect on loss model parameters. Consequently, the next step of my research involved performing variable selection on the predictor candidates and training regression models across flood pathways.

In training (or fitting) a numerical model, one does not merely assemble an estimation tool. The development of numerical models also improves one's understanding of the modelled process. Variable selection helps to filter the most important factors that influence financial loss ratio, removing non-identifiable variables ('noise') and increasing generalisability (McElreath, 2020). The goals of my selection process were exploring and learning, rather than achieving simulation efficiency, meaning that the selection process favoured the identification of a greater number of explaining variables. The selection included characteristics of the hazard, affected building, and indicators of preparedness (Table 6.1). The inclusion of indicators of preparedness – although rarely included in loss models (Gerl et al., 2016) – comports with other conceptual works that have advocated for greater focus on the 'resistance' (Thieken et al., 2005), on the vulnerability side of the loss equation (Mechler & Bouwer, 2015), and on the population behaviour vias-à-vis risk (Bubeck et al., 2012). This differs from the common focus on the hazard component. In comparing their relevance to flood pathways, the selected variables are of varying importance and contribution levels across flood pathways; however, three dimensions (hazard, building, and preparedness) were deemed to be relevant to each flood pathway (see Table 3.6). Furthermore, exposure data, which is crucial for loss estimation, has benefited from recent developments in open data sets (see Sieg et al., 2019). However, there has been a reported improvement in flood preparedness in Germany (Kienzler et al., 2015; Kreibich et al., 2011; Thieken, Bessel et al., 2016); nonetheless, these indicators are still not monitored regularly, which suggests a need for regular and systematically organised data collection (from chapter 3).

Although multiple linear regression is very versatile, the technique has its limitations. I advance my study by training BMMs with partial pooling in order to learn multiple settings (different flood pathways, different socioeconomic regions, or different flood events/years) simultaneously.

6.2.3 How well can Bayesian loss models learn from different settings?

Instead of learning different models for different settings – that is, splitting the data and using only small portions of the data for each group (e.g. households affected by each flood pathway) – special techniques can be used to learn different parameters for different groups simultaneously. One such technique is BMM, which bears many advantages. The incorporation of prior knowledge offers a form of penalisation that can reduce overfitting. By employing hyperparameters, that link each group-level parameter (i.e. model parameters that are specific to each group), each group informs all other groups; in essence, this utilises more data. Bayesian models are probabilistic by nature and intrinsically incorporate uncertainty, providing a more complete view of a modelled process. Because this modelling approach is different from the previous development (Mohor et al., 2020), Mohor et al. (2021) accomplish a new variable selection based on the set of predictors selected by Mohor et al. (2020). The number of predictors was reduced from 12 to seven in an effort to achieve the ideal balance between predictive accuracy and generalisation. As in the previous study, the three dimensions (hazard, building, and preparedness) were selected (Table 6.1). The influence of three different settings (flood pathways, socioeconomic regions, and flood events) was investigated since it was assumed that these settings allow some insights into the transferability of loss models. Although the priors for the predictors' coefficients were centred at zero (weak priors), most regression coefficients were credible (i.e. the 90% highest density interval [HDI] is above [or below] zero; see Figures 4.3, 4.4, and 4.5). The hyperparameters potentially caused group-level parameters to shrink. Nonetheless, in the three model variants, several learned regression coefficients were credibly different for different groups, showing the BMMs' ability to differentiate between the effects of predictors for different settings.

However, across different events, the model variant revealed many non-credible coefficients. This is potentially due in part to the small size of the subgroups, which results in larger uncertainty, but also to the fact that this data split may be unrelated to the damaging processes; the model retains mixed processes (for example, the dynamics of different flood pathways) within smaller samples. Similarly, the coefficients for the socioeconomic regions all overlapped, and the coefficients for the smallest group (the smallest data sample) were inconclusive. Conversely, many credible differences were found across flood pathways in six out of seven predictors, namely: flood water depth, contamination, duration, implementation of property-level precautionary measures (PLPMs), insurance, and previous flood experience. Flood pathways are likely to override socioeconomic differences and are more informative regarding the loss damaging process than other groupings.

The BMMs' ability to balance previous knowledge and new data, account for uncertainty, and learn different settings at the same time may offer a way forward in improving model transferability. Mohor et al. (2021, chapter 4) analysis illustrates that flood pathways likely deserve more attention than regional or temporal characteristics. On the one hand, this finding paves the way for future research. On the other hand, this supports the identification of the flood pathways that have been addressed in previous (and future) loss datasets and loss models and raises awareness of this relevant dimension in model transferability applications.

6.2.4 Do compound, that is, coinciding flood pathways result in higher losses than a single pathway, and what does the outcome imply for future loss modelling?

BMMs are highly useful due to the versatility of structures that one can create with them. This assists in the representation of compound (inland) floods, when multiple flood pathways affect the same asset during the same event; this can happen simultaneously or consecutively (notably, the data used in this paper do not capture this). This set of coinciding flood pathways can be integrated either through multi-membership or through specific combinations. The two structures, however, answer different questions and pose different challenges.

A multi-membership structure can learn parameters for each individual flood pathway in a compound flood. However, it requires not only that one correctly identify the pathways but also determine the proportional amounts each pathway contributes to the final compound loss. The dataset used only includes the total or maximal value of each variable for the flood events and does not distinguish between the characteristics of each coinciding pathway, let alone provide their contribution proportions. My attempt to use the proportions from the general loss ratio of each pathway resulted in small changes in model parameters and loss estimates (Mohor et al., submitted; chapter 5). A potential way forward is to use hydraulic models and examine the proportion of water depth (the dominant predictor) of each pathway as the proportional factor for all other variables.

The model variant's combinations of flood pathways, which form specific compound categories, obviates the need to assign weights to the contributions of individual pathways. Instead, it learns model parameters for specific compound floods (i.e. each specific combination of flood pathways), not for each individual pathway. The loss estimates from this model variant could potentially answer whether there are synergetic effects (i.e.

whether compound inland floods lead to higher losses compared to the individual flood pathways). The probability distribution of loss estimates from this model, like the other models, is wide. Credible differences between loss estimates from compound events and from individual pathways were not observed. A general reduction in uncertainty of the loss estimates is therefore necessary to provide a conclusive answer regarding the synergetic effect on loss.

6.3 Constraints

This study used a large dataset of 6000 datapoints from eight cross-sectional post-flood surveys across Germany. Kienzler et al. (2015) and Thieken et al. (2010) have identified potential data biases, such as age and property ownership. Although the effect of these biases is small, it is worth noting that they are of importance. First, survey respondents needed a landline telephone to respond to the survey, resulting in an older average respondent age. Second, given the selection and sampling method, it was likely not possible to reach residents of highly damaged or destroyed buildings. Third, the dataset does not include buildings within an affected area which did not report financial losses, which could provide valuable insights into the efficacy of protective behaviours and property-level defence measures. Additionally, as discussed in section 3.3.1.2, the presence of cellars at groundwater-flood affected buildings introduces a potential exposure bias. However, Germany still lacks a census database that could be used to verify the existence of this latter of bias.

It is highly recommended that future studies gather data on non-affected households in flood-affected areas to better understand the 'exposure' side of the equation (i.e. who is affected and who is not). This thesis assumed a near-perfect knowledge of exposure, which is unfeasible for real risk assessments. This development, though necessary, was outside the scope of the developments presented here.

It is important to note that across flood events, the model variant developed in chapter 4, is not temporally based or non-stationary. The year was used as an indicator for each event and as a grouping variable. Further studies could explore non-stationarity in loss models, as this remains an unstudied topic.

Two issues were pertinent to all chapters and developments: the identification of flood pathways and potential non-linear, moderated, or mediated effects.

It is surprising that features of the warning system were not relevant for loss estimation in the model, despite that it has been shown that having time to act makes a difference in reducing the impact of a flood event; however, at the same time, one's first action in the event of a flood should be physical safety, not safeguarding assets (Penning-Rowsell, 2005), and a warning alone may not be effective if a person does not know how to act (Kreibich et al., 2021). It is reasonable to conclude that warning indicators alone have only an indirect effect on financial loss, while indicators of preparedness (e.g., experience and implemented emergency and precautionary measures) are more closely associated with the damaging process. This can be the result of moderated or mediated effects. In-depth explorations of such effects are suggested for future research.

Sub-classifications of floods are still diversely and ambiguously defined (see chapter 1). In chapter 2, two flood events were analysed in detail, but in chapters 3 to 5, data from eight flood events were used, and the identification of flood pathways relied on the respondents' observations and several cross-checks. However, this process was not exhaustively done. Although it is unlikely that one will be able to obtain unambiguous definitions, clear definitions are nonetheless desirable in performing such classifications. More importantly, multiple flood pathways occur during a flood event. Differentiating each pathway's contribution and identifying the synergetic effect of a compound flood on financial loss remains challenging without the differentiation of individual pathways. This challenge is even greater when pathways coincide rather than occur consecutively. The use of hydraulic models is promising, as has been shown in examinations of fluvial-coastal compound floods, but the hydraulic modelling of surface water floods and groundwater floods lags behind the modelling of river floods; this must be improved if compound inland flood scenarios are to be created and investigated.

6.4 Conclusion

Across flood pathways, the models applied learned credibly different coefficients for most (six out of seven) predictors, namely: flood water depth, contamination, duration, implementation of property-level precautionary measures, insurance, and previous flood experience (Chapter 4; see Mohor et al., 2021). In other words, the characteristics of a flood and the indicators of preparedness result in differing levels of loss to residential buildings within different flood pathways.

The different contribution levels of various indicators of preparedness to the loss ratio may be related to the magnitude, frequency, or erraticness of the flood pathways. For example, levee breaches are typically severe floods; surface water floods may happen anywhere, thus, risk maps are not broadly produced, and weather forecasting has typically a short lead time. Although statistic and probabilistic models do not prove causality, the relevance of preparedness (indicators) for loss estimation was reinforced, thus highlighting the need for their inclusion in data collection, further studies on their representativeness in datasets, and their role in loss estimation. If multivariable models such as the ones presented in this thesis were to be applied in a new situation, input data such as water level and flood duration can be derived from hydraulic modelling and hazard scenarios.

However, information such as insurance purchasing and PLPMs implementation would have to be estimated from proxy variables, since there is no database that includes such information at the micro-level.

Continuous (or regular and systematic) data recording is crucial for the continuous improvement of loss modelling and risk assessment in general. The findings of this thesis contribute to this end by identifying which data are the most relevant and thus should be collected (Table 6.1), helping conserve resources. However, one alternative approach is to identify proxy variables that could be incorporated into loss models; these variables may occur or apply at different spatial scales. For example, regional insurance coverage can be a proxy for household insurance, a flood database can provide an estimate for flood experience, and census data (Pittore et al., 2020) and open data (Sieg et al., 2019) can inform exposure and asset values. Moreover, new developments in behavioural models can inform preparedness and PLPMs implementation (Bubeck et al., 2020).

Regarding data collection, several loss models use claim data as a proxy for financial loss. Insurance and governmental claims serve as proxies in many cases, as they often account for an amount that is less than the total loss; for instance, by discounting deductibles or losses that are not covered by the insurance policy. Although such biases could, in principle, be corrected, in studies that involve large areas, it is likely that different insurance policy contracts will differ from one another. In most cases, this will lead to values that are under-representative of the actual loss. Additionally, loss numbers may be based on market values or reconstruction values (Molinari et al., 2020), methodologies that may not be fully compatible with one another. Therefore, determining what information must be collected and ensuring sufficient documentation of data collection and usage is crucial (Molinari et al., 2020).

On that topic, the database used in this thesis was valuable, as it included the actual repair and replacement costs reported by the residents at the object level. Furthermore, it also included preparedness indicators and the PLPMs implemented, an information that is not regularly collected, as well as the identification of flood pathways, which this thesis discussed, remains an under-explored but relevant aspect of loss modelling.

Take-home message Flood pathways (levee breaches, river floods, surface water floods, and groundwater floods) are more representative of flood characteristics at the immediacy of impacted assets than commonly addressed flood types (pluvial, fluvial, and coastal), which are relevant for loss estimation. The known factors that explain financial loss (i.e. characteristics of the hazard load and indicators of preparedness – the resistance side of the equation) have different effects (in magnitude) for different flood pathways. The identification and characterisation of flood pathways, especially when such pathways coincide in compound events, must still be improved in support of loss modelling.

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Appendices

Appendix A

Appendix to Chapter 3

It is sometimes suggested (Hair et al., 2019) that more, rather than less, variables should be retained in a regression when explanation is aimed rather than prediction. Therefore, we selected not only the most prominent variables in our selection process but also those more relevant in previous works, under non-linear and non-parametric methods (Merz et al., 2013; Schröter et al., 2014; Vogel et al., 2014; Vogel et al., 2018), since a great reduction of variables have been already achieved, as well as a good ratio between data points and number of variables. From these works we observed only those predictors selected more than once in at least one method (in at least one of): a) Bayesian Network-based (BN), Markov-Blanket (MB), and a sum score of flood-type-specific and event-specific MBs, or b) Bagging-Tree and the two BN runs for 2002-2006 data only (see Table A.1). Out of the nine selected variables, seven agreed with our results. Among our potential predictors, the year of the event and the quality of the affected building were also repeatedly included in the abovementioned works and added to our set. However, the year of the event is less fit for transferability exercises based on a linear regression, only building quality was added to our 12 initially selected variables.

Table A.1: Variables selected in different models from the same or similar dataset towards building loss ratio modeling

Predictor	BN (2002-2013) (Vogel et al. 2018)			BN (2002-2006)		Bagging-Tree (2002-2006)
	sum>1	BN based	MB[1]	Vogel 2013	Schröter 2014[2]	
Year	X	X	X			
Water Depth	X	X	X	X	X	X
Duration	X		X	X	X	X
Velocity Indicator	X	X		X		X

Variables selected in different models from the same or similar dataset towards building loss ratio modeling (continued)

Predictor	BN (2002-2013) (Vogel et al. 2018)			BN (2002-2006)		Bagging-Tree (2002-2006)
	sum>1	BN based	MB[1]	Vogel 2013	Schröter 2014[2]	
Contamination	X	X	X	X	X	X
Warning lead time		X		X		
W. quality				X		
W. source						
W. information						
Gap Warn-Action		X				
Emergency				X		
Precautionary	X	X		X	X	X
Efficiency Pre		X		X		
Flood Exp Class	X			X		
Awareness				X		
Building type	X				X	
N of Flats						
Building area	X (b.value)	X (b.value)	X (b.value)		X (b.value)	X (b.value)
House/Flat area						
Building quality	X	X		X	X	
Age						
Household						
Children						
Elderly						
Ownership		X				
Income class						
Socio-Economic Class						
Insured		X				
Federal State						
Flood Type	X	X	X			
Return period[3]					X	X

[1] at least 2 of 4 methods
[2] "expert knowledge" 10b
[3] not available in this study

Table A.2: Regression coefficients and notation, statistical significance, and std. error for Generalized Linear Regression (Gaussian distribution, identity link)

	Levee_1	River_2	Surface_3	Ground_4	All Flood Type	All FT + Year
(Intercept)	0.3667 *** (0.0785)	0.2776 *** (0.0359)	0.2648 ** (0.0867)	0.2050 *** (0.0402)	0.3193 *** (0.0276)	0.3210 *** (0.0277)
WaterDepth	0.0005 *** (0.0001)	0.0003 *** (0.0000)	0.0002 *** (0.0000)	0.0003 *** (0.0000)	0.0003 *** (0.0000)	0.0003 *** (0.0000)
Duration	0.0103 (0.0058)	0.0120 *** (0.0029)	0.0161 * (0.0063)	0.0042 (0.0023)	0.0113 *** (0.0020)	0.0107 *** (0.0021)
Velocity	0.0045 (0.0036)	0.0026 (0.0019)	0.0057 (0.0046)	-0.0004 (0.0021)	0.0032 * (0.0014)	0.0033 * (0.0014)
Contamination	0.0360 *** (0.0090)	0.0198 *** (0.0056)	0.0537 *** (0.0125)	0.0039 (0.0079)	0.0279 *** (0.0041)	0.0278 *** (0.0041)
Emergency	-0.0003 (0.0016)	-0.0014 (0.0008)	-0.0023 (0.0019)	-0.0005 (0.0010)	-0.0014 * (0.0006)	-0.0013 * (0.0006)
Precautionary	0.0011 (0.0103)	-0.0171 *** (0.0049)	-0.0220 (0.0119)	-0.0162 ** (0.0053)	-0.0147 *** (0.0037)	-0.0130 ** (0.0041)
EfficiencyPre	0.0069 (0.0039)	0.0027 (0.0021)	0.0063 (0.0054)	0.0022 (0.0025)	0.0039 * (0.0016)	0.0039 * (0.0016)
FloodExpClass	-0.0231 ** (0.0070)	-0.0034 (0.0030)	0.0095 (0.0073)	-0.0004 (0.0035)	-0.0042 (0.0023)	-0.0032 (0.0024)
BuildingArea	-0.0717 *** (0.0124)	-0.0478 *** (0.0060)	-0.0447 ** (0.0156)	-0.0280 *** (0.0069)	-0.0517 *** (0.0046)	-0.0515 *** (0.0046)
BuildQuality	-0.0054 (0.0080)	-0.0058 (0.0039)	-0.0201 * (0.0093)	-0.0063 (0.0045)	-0.0076 ** (0.0029)	-0.0071 * (0.0030)
NoCellar	0.0195 (0.0165)	0.0096 (0.0087)	0.0293 (0.0205)	0.0171 (0.0139)	0.0152 * (0.0066)	0.0148 * (0.0066)
Insured	0.0372 ** (0.0130)	0.0186 ** (0.0069)	-0.0210 (0.0162)	-0.0016 (0.0076)	0.0152 ** (0.0051)	0.0143 ** (0.0052)
Riverine Flood (1)					-0.0258 *** (0.0071)	-0.0255 *** (0.0072)
Surface water Flood (1)					-0.0162 (0.0101)	-0.0171 (0.0103)
Groundwater (1)					-0.0298 ** (0.0096)	-0.0312 ** (0.0098)
Year2005 (2)						-0.0031 (0.0131)
Year2006 (2)						-0.0248 (0.0178)
Year2010 (2)						-0.0118

	Levee_1	River_2	Surface_3	Ground_4	All Flood Type	All FT + Year
						(0.0091)
Year2011 (2)						-0.0205
						(0.0133)
Year2013 (2)						0.0001
						(0.0072)
N	368	976	217	251	1812	1812
AIC	-492.1	-1601.7	-311.9	-709.8	-2956.5	-2952.2
BIC	-437.4	-1533.3	-264.6	-660.4	-2862.9	-2831.2
Adjusted R2[3]	0.3981	0.2751	0.3777	0.3092	0.3701	0.3703

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

[1] Levee breach as reference level

[2] Year 2002 as reference level

[3] The R-package used here do not calculate the adjusted R^2 to the referred models, but it was manually calculated and added to the table

Table A.3: Standardized coefficient estimates of the Levee Breach-specific-regression with confidence interval and Variance inflation factor (VIF), ordered by estimate magnitude

	Est.	5%	95%	t val.	p	VIF
(Intercept)	0.146	0.129	0.162	14.689	0.000	NA
WaterDepth	0.065	0.054	0.076	9.364	0.000	1.198
BuildingArea	-0.038	-0.048	-0.027	-5.772	0.000	1.057
Insured	0.037	0.016	0.059	2.864	0.004	1.047
Contamination	0.026	0.016	0.037	4.000	0.000	1.088
FloodExpClass	-0.022	-0.033	-0.011	-3.286	0.001	1.130
NoCellar	0.019	-0.008	0.047	1.180	0.239	1.158
Duration	0.012	0.001	0.024	1.779	0.076	1.181
EfficiencyPre	0.012	0.001	0.023	1.780	0.076	1.153
Velocity	0.008	-0.003	0.019	1.234	0.218	1.069
BuildQuality	-0.004	-0.015	0.006	-0.677	0.499	1.057
Emergency	-0.001	-0.013	0.010	-0.212	0.832	1.138
Precautionary	0.001	-0.011	0.013	0.104	0.917	1.288

Table A.4: Standardized coefficient estimates of the Riverine-specific-regression with confidence interval and Variance inflation factor (VIF), ordered by estimate magnitude

	Est.	5%	95%	t val.	p	VIF
(Intercept)	0.077	0.068	0.085	14.461	0.000	NA
WaterDepth	0.045	0.039	0.051	11.924	0.000	1.257
BuildingArea	-0.027	-0.033	-0.022	-7.997	0.000	1.027
Insured	0.019	0.007	0.030	2.684	0.007	1.048
Duration	0.015	0.009	0.021	4.188	0.000	1.103
Precautionary	-0.014	-0.020	-0.007	-3.470	0.001	1.371
Contamination	0.013	0.007	0.019	3.524	0.000	1.138
NoCellar	0.010	-0.005	0.024	1.107	0.268	1.155
Emergency	-0.006	-0.012	-0.001	-1.795	0.073	1.107
BuildQuality	-0.005	-0.011	0.001	-1.493	0.136	1.024
Velocity	0.005	-0.001	0.010	1.372	0.170	1.057
EfficiencyPre	0.004	-0.001	0.010	1.270	0.204	1.068
FloodExpClass	-0.004	-0.011	0.002	-1.153	0.249	1.292

Table A.5: Standardized coefficient estimates of the Surface water-specific-regression with confidence interval and Variance inflation factor (VIF), ordered by estimate magnitude

	Est.	5%	95%	t val.	p	VIF
(Intercept)	0.106	0.087	0.124	9.358	0.000	NA
WaterDepth	0.041	0.026	0.056	4.501	0.000	1.404
Contamination	0.037	0.023	0.051	4.290	0.000	1.240
NoCellar	0.029	-0.004	0.063	1.430	0.154	1.129
BuildingArea	-0.023	-0.036	-0.010	-2.871	0.005	1.073
Duration	0.022	0.008	0.037	2.570	0.011	1.268
Insured	-0.021	-0.048	0.006	-1.292	0.198	1.066
BuildQuality	-0.018	-0.031	-0.004	-2.156	0.032	1.100
Precautionary	-0.016	-0.031	-0.002	-1.844	0.067	1.317
FloodExpClass	0.011	-0.003	0.025	1.303	0.194	1.205
Velocity	0.011	-0.003	0.025	1.253	0.212	1.253
Emergency	-0.010	-0.023	0.004	-1.205	0.230	1.126
EfficiencyPre	0.009	-0.004	0.023	1.152	0.251	1.125

Table A.6: Standardized coefficient estimates of the Ground water-specific-regression with confidence interval and Variance inflation factor (VIF), ordered by estimate magnitude

	Est.	5%	95%	t val.	p	VIF
(Intercept)	0.036	0.028	0.045	7.415	0.000	NA
WaterDepth	0.032	0.025	0.039	7.550	0.000	1.398
NoCellar	0.017	-0.006	0.040	1.231	0.220	1.329
BuildingArea	-0.015	-0.021	-0.009	-4.028	0.000	1.069
Precautionary	-0.013	-0.020	-0.006	-3.049	0.003	1.390
Duration	0.007	0.001	0.013	1.814	0.071	1.157
BuildQuality	-0.005	-0.011	0.001	-1.402	0.162	1.042
EfficiencyPre	0.003	-0.003	0.009	0.859	0.391	1.065
Contamination	0.002	-0.005	0.009	0.485	0.628	1.221
Emergency	-0.002	-0.008	0.004	-0.504	0.615	1.106
Insured	-0.002	-0.014	0.011	-0.213	0.832	1.083
Velocity	-0.001	-0.007	0.006	-0.182	0.856	1.088
FloodExpClass	-0.001	-0.007	0.006	-0.122	0.903	1.371

Table A.7: Standardized coefficient estimates of the overall regression with confidence interval and Variance inflation factor (VIF), ordered by estimate magnitude

	Est.	5%	95%	t val.	p	VIF
(Intercept)	0.109	0.098	0.120	16.118	0.000	NA
WaterDepth	0.050	0.045	0.055	16.954	0.000	1.381
FloodTypeGround_4	-0.030	-0.046	-0.014	-3.110	0.002	1.579
BuildingArea	-0.029	-0.033	-0.024	-11.322	0.000	1.023
FloodTypeRiver_2	-0.026	-0.037	-0.014	-3.610	0.000	1.579
Contamination	0.019	0.014	0.023	6.881	0.000	1.195
Duration	0.016	0.012	0.021	5.688	0.000	1.339
FloodTypeSurface_3	-0.016	-0.033	0.001	-1.594	0.111	1.579
Insured	0.015	0.007	0.024	2.970	0.003	1.052
NoCellar	0.015	0.004	0.026	2.300	0.022	1.134
Precautionary	-0.012	-0.016	-0.007	-3.970	0.000	1.365
BuildQuality	-0.007	-0.011	-0.002	-2.593	0.010	1.023
EfficiencyPre	0.007	0.002	0.011	2.495	0.013	1.091
Emergency	-0.006	-0.010	-0.002	-2.324	0.020	1.108
Velocity	0.006	0.002	0.010	2.280	0.023	1.108
FloodExpClass	-0.005	-0.010	0.000	-1.811	0.070	1.306

Table A.8: Pairwise comparison of predictor variables across flood types through Dunn's test or pairwise Chi-Squared test for continuous and nominal variables, respectively, after Holm's correction of p-Value for multiple comparison

Variable	p-Value of pairwise comparison			
Water Depth		Levee	River	Flash
	River	0		
	Flash	0	0.959	
	Ground	0	0.000	0
Duration		Levee	River	Flash
	River	0		
	Flash	0	0.000	
	Ground	0	0.643	0
Velocity		Levee	River	Flash
	River	0.859		
	Flash	0.000	0	
	Ground	0.000	0	0
Contamination		Levee	River	Flash
	River	0.0000		
	Flash	0.0024	0.0017	
	Ground	0.0000	0.0000	0
Warn. Lead-Time		Levee	River	Flash
	River	0		
	Flash	0	0.000	
	Ground	0	0.446	0
Warn. Quality		Levee	River	Flash
	River	0.00		
	Flash	0.26	0.0446	
	Ground	0.00	0.5060	0.0446
Warn. Info		Levee	River	Flash
	River	0		
	Flash	0	0e+00	
	Ground	0	1e-04	9e-04
Warn. Source		Levee	River	Flash
	River	0		
	Flash	0	0e+00	
	Ground	0	7e-04	0
Gap Warn.-Action		Levee	River	Flash
	River	0.0000		
	Flash	0.0133	0.719	
	Ground	0.3980	0.398	0.398

Variable	p-Value of pairwise comparison			
Emergency		Levee	River	Flash
	River	0.0286		
	Flash	0.1690	0.0002	
	Ground	0.5170	0.0131	0.517
Precautionary		Levee	River	Flash
	River	0.000		
	Flash	1.000	0	
	Ground	0.751	0	1
Efficiency Pre.		Levee	River	Flash
	River	0e+00		
	Flash	2e-04	0.962	
	Ground	0e+00	0.470	0.962
Flood Experience Class		Levee	River	Flash
	River	0.0000		
	Flash	0.0184	0	
	Ground	0.0002	0	0.284
Awareness of flood risk		Levee	River	Flash
	River	0.2800		
	Flash	0.0001	0	
	Ground	0.0167	0	0.28
Ownership		Levee	River	Flash
	River	0.0111		
	Flash	0.0097	0.161	
	Ground	0.0002	0.161	0.451
Build. Type		Levee	River	Flash
	River	0.0000		
	Flash	0.0000	0.0057	
	Ground	0.0032	0.8140	0.0848
Number of Flats		Levee	River	Flash
	River	0.0000		
	Flash	0.0001	0.557	
	Ground	0.1190	0.123	0.123
Build.Quality		Levee	River	Flash
	River	0.1010		
	Flash	0.5490	0.6870	
	Ground	0.0007	0.0488	0.0918
Build. Value		Levee	River	Flash
	River	0.0002		
	Flash	0.0050	1	
	Ground	0.0157	1	1

Variable	p-Value of pairwise comparison			
House or flat area		Levee	River	Flash
	River	0.473		
	Flash	1.000	1.000	
	Ground	1.000	0.225	1
Building area		Levee	River	Flash
	River	0.0000		
	Flash	0.0002	0.555	
	Ground	0.0185	0.555	0.544
No Cellar		Levee	River	Flash
	River	1		
	Flash	1	1	
	Ground	0	0	0.004
Age		Levee	River	Flash
	River	0.272		
	Flash	0.979	0.4190	
	Ground	0.348	0.0027	0.419
Household size		Levee	River	Flash
	River	1.00		
	Flash	1.00	0.818	
	Ground	0.59	0.264	1
Children		Levee	River	Flash
	River	0.5380		
	Flash	0.1840	0.538	
	Ground	0.0343	0.154	0.615
Elderly		Levee	River	Flash
	River	0.96		
	Flash	0.72	0.720	
	Ground	0.72	0.603	0.197
Income Class		Levee	River	Flash
	River	0.080		
	Flash	0.660	0.080	
	Ground	0.007	0.163	0.0078
Socioeconomic Class		Levee	River	Flash
	River	0.986		
	Flash	0.986	0.874	
	Ground	0.874	0.177	0.986
Insured		Levee	River	Flash
	River	1.0000		
	Flash	0.0587	0.0587	
	Ground	0.0587	0.0587	1

Variable	p-Value of pairwise comparison			
Region		Levee	River	Flash
	River	0		
	Flash	0	0.000	
	Ground	0	0.026	0.0057
Year		Levee	River	Flash
	River	0		
	Flash	0	0	
	Ground	0	0	0
Loss ratio		Levee	River	Flash
	River	0		
	Flash	0	0.91	
	Ground	0	0.00	0
bloss_2013		Levee	River	Flash
	River	0		
	Flash	0	0.895	
	Ground	0	0.000	0

Appendix B

Appendix to Chapter 4

Table B.1: Comparison of candidate models of each variants by their difference in the expected log pointwise predictive density (elpd) to first model (fit1) and the standard error of the differences; model candidates with cumulative predictors from 1 to 12

Single-level				Flood Type				Region				Event			
Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff
fit1	1986.4	0	0	fit1	2018.68	0	0	fit1	2002.60	0	0	fit1	2036.28	0	0
fit2	2033.8	47.34	9.56	fit2	2057.33	38.65	8.72	fit2	2041.76	39.16	8.60	fit2	2074.17	37.89	8.55
fit3	2079.6	93.15	13.88	fit3	2093.22	74.54	12.45	fit3	2085.28	82.67	13.14	fit3	2109.95	73.67	13.26
fit4	2092.3	105.81	15.3	fit4	2098.06	79.37	12.84	fit4	2094.31	91.71	14.49	fit4	2122.40	86.13	14.51
fit5	2109.8	123.33	16.11	fit5	2113.37	94.69	13.62	fit5	2107.96	105.36	15.14	fit5	2126.39	90.11	14.95
fit6	2118.1	131.61	16.41	fit6	2124.02	105.34	14.10	fit6	2111.94	109.33	15.50	fit6	2130.38	94.11	15.46
fit7	2122.9	136.47	16.68	fit7*	2127.00	108.32	14.50	fit7	2115.93	113.32	15.68	fit7*	2132.51	96.23	15.72
fit8*	2122.0	135.54	16.65	fit8*	2125.44	106.76	14.53	fit8*	2115.38	112.78	15.66	fit8*	2130.47	94.19	15.69
fit9*	2124.0	137.5	16.93	fit9*	2126.19	107.51	14.82	fit9*	2117.35	114.75	16.19	fit9*	2132.64	96.36	15.43
fit10*	2125.1	138.69	16.88	fit10*	2125.88	107.20	14.78	fit10*	2120.50	117.90	16.25	fit10*	2133.34	97.06	15.64
fit11	2130.5	144.02	16.91	fit11	2131.83	113.15	15.11	fit11*	2122.01	119.40	16.23	fit11*	2133.62	97.34	15.61
fit12	2134.6	148.14	16.99	fit12*	2134.26	115.58	15.26	fit12*	2125.23	122.62	16.26	fit12*	2134.36	98.08	15.72

* Model complexity after which little gain is observed (elpd_diff <4)

Table B.2: Comparison of candidate models of each variants by their difference in the expected log pointwise predictive density (elpd) to the reference model fit6 (by each model variant) and the standard error of the differences; model candidates with predictors 1 to 6 plus one of the remaining predictors

Single-level				Flood Type				Region				Event			
Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff
fit6+8	2117.3	-0.8	0.2	fit6+8	2122.3	-1.7	0.5	fit6+8	2111.7	-0.3	1.1	fit6+8	2129	-1.4	0.4
fit6	2118.1	0	0	fit6+10	2123.2	-0.9	1.4	fit6	2111.9	0	0	fit6+11	2130	-0.3	1.7
fit6+10	2118.9	0.8	2.1	fit6	2124	0	0	fit6+12	2113.2	1.2	2.4	fit6	2130.4	0	0
fit6+9	2119.9	1.9	2.6	fit6+12	2124.2	0.2	2.0	fit6+9	2114.7	2.7	3.3	fit6+10	2131.1	0.7	2.1
fit6+12	2121.3	3.3	2.9	fit6+9	2124.4	0.3	2.0	fit6+11	2115	3.1	2.8	fit6+12	2131.2	0.8	2.1
fit6+7 *	2122.9	4.9	3.6	fit6+7	2127	3.0	3.5	fit6+10	2115.6	3.6	3.2	fit6+9	2132.1	1.7	3.0
fit6+11*	2123	5.0	3.3	fit6+11*	2130.8	6.7	3.9	fit6+7*	2115.9	4.0	3.4	fit6+7	2132.5	2.1	3.0

* Model with relevant improvement compared to others (elpd_diff > 4 and elpd_diff > se_diff)

Table B.3: Comparison of candidate models of each variants by their difference in the expected log pointwise predictive density (elpd) to the reference model (fit6) and the standard error of the differences; model candidates with predictors 1 to 5 plus a combination of predictors 6, 7, and 11

Single-level				Flood Type				Region				Event			
Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff	Model	elpd_loo	elpd_diff	se_diff
fit5+7*	2114.5	-3.6	5.7	fit5+7	2117.8	-6.2	6.1	fit5+11*	2111	-0.9	4.2	fit5+11	2126.1	-4.3	4.0
fit5+11*	2115	-3.1	5.5	fit5+11*	2120.5	-3.5	6.4	fit5+7*	2111.7	-0.2	4.7	fit5+7*	2128.1	-2.3	4.6
fit6*	2118.1	0	0	fit6*	2124	0	0	fit6*	2111.9	0	0	fit5+7+11*	2129	-1.4	5.0
fit5+7+11*	2119.7	1.6	6.7	fit5+7+11*	2124.1	0.1	7.4	fit5+7+11*	2114.2	2.3	5.5	fit6+11*	2130	-0.3	1.7
fit6+7	2122.9	4.9	3.5	fit6+7*	2127	3	3.5	fit6+11*	2115	3.1	2.8	fit6*	2130.4	0	0
fit6+11	2123	5.0	3.3	fit6+11	2130.8	6.7	3.9	fit6+7	2115.9	4.0	3.4	fit6+7+11*	2131.9	1.5	3.5
fit6+7+11	2127.6	9.6	4.8	fit6+7+11	2133.6	9.6	5.4	fit6+7+11	2118.3	6.4	4.3	fit6+7*	2132.5	2.1	3.0

* Models with predictive accuracy that is indistinguishable from that of the reference model fit6

Table B.4: Central values of each variable per event grouped by similarity after post hoc tests with a significance of 0.05 (central value is the average of numeric Variables, the mode of nominal variables)

EVENT	2002		2005		2006		2010		2011		2013	
n	1697		305		156		440		218		1652	
Water depth	64.212	a	-19.351	b	18.816	b,c	24.669	c	-23.271	b,c	53.526	d
Duration	142.89	a	52.371	b	146.18	c	57.962	b	101.21	a	206.04	d
Velocity	32.326	a	29.304	a,b	26.533	b,c	33.535	a	23.876	b,c	24.833	c
Contamination	0.67265	a	0.27	b	0.35099	b,c	0.54801	d	0.25463	b,c	0.45702	c
Loss ratio	0.12262	a	0.040601	b	0.069922	b,c	0.077278	c	0.019505	d	0.11732	a

[a–d] Notation of subsamples that are statistically similar to each other; same letters mean similar subsamples; two letters next to a central value means it is similar to both letters' groups (see text for reading example)

Appendix C

Appendix to Chapter 5

Table C.1: Pairs of coefficients with 90% credible differences within each model variant

Model variant	Variable	Difference in flood pathways estimates	Median of difference	Fraction of distribution beyond zero
Baseline	Intercept	pLevee-pSurface	0.41	>99.5%
Baseline	Intercept	pLevee-pGround	0.35	97%
Baseline	Intercept	pRiver-pSurface	0.32	>99.5%
Baseline	Intercept	pRiver-pGround	0.27	96%
Baseline	WaterDepth	pLevee-pSurface	0.25	>99.5%
Baseline	WaterDepth	pRiver-pSurface	0.22	>99.5%
Baseline	WaterDepth	pSurface-pGround	-0.23	4%
Baseline	BuildingArea	pRiver-pSurface	-0.09	5%
Baseline	Insured	pLevee-pRiver	0.15	91%
Baseline	FloodExperience	pLevee-pSurface	-0.13	7%
UniformW	Intercept	pLevee-pSurface	0.45	99%
UniformW	Intercept	pLevee-pGround	0.49	99%
UniformW	Intercept	pRiver-pSurface	0.42	>99.5%
UniformW	Intercept	pRiver-pGround	0.45	>99.5%
UniformW	WaterDepth	pLevee-pSurface	0.28	>99.5%
UniformW	WaterDepth	pRiver-pSurface	0.24	>99.5%
UniformW	WaterDepth	pSurface-pGround	-0.2	3%
UniformW	Contamination	pRiver-pSurface	-0.14	7%
UniformW	FloodExperience	pLevee-pSurface	-0.17	4%
UniformW	FloodExperience	pLevee-pGround	-0.13	8%
DefinedW	Intercept	pLevee-pSurface	0.44	99%
DefinedW	Intercept	pLevee-pGround	0.48	99%

Pairs of coefficients with 90% credible differences within each model variant (continued)

Model variant	Variable	Difference in flood pathways estimates	Median of difference	Fraction of distribution beyond zero
DefinedW	Intercept	pRiver-pSurface	0.41	>99.5%
DefinedW	Intercept	pRiver-pGround	0.44	>99.5%
DefinedW	WaterDepth	pLevee-pSurface	0.27	>99.5%
DefinedW	WaterDepth	pRiver-pSurface	0.24	>99.5%
DefinedW	WaterDepth	pSurface-pGround	-0.2	4%
DefinedW	Contamination	pRiver-pSurface	-0.14	8%
DefinedW	FloodExperience	pLevee-pSurface	-0.17	6%
DefinedW	FloodExperience	pLevee-pGround	-0.13	9%
Combined	Intercept	pLevee.0.0.0-0.0.pSurface.0	0.33	99%
Combined	Intercept	pLevee.0.0.0-0.0.0.pGround	0.31	97%
Combined	Intercept	pLevee.0.0.0-0.pRiver.0.pGround	0.21	91%
Combined	Intercept	pLevee.0.0.0-0.0.pSurface.pGround	0.29	95%
Combined	Intercept	0.pRiver.0.0-0.0.pSurface.0	0.29	>99.5%
Combined	Intercept	0.pRiver.0.0-0.0.0.pGround	0.27	98%
Combined	Intercept	0.pRiver.0.0-0.0.pSurface.pGround	0.26	96%
Combined	Intercept	pLevee.pRiver.0.0-0.0.pSurface.0	0.4	99%
Combined	Intercept	pLevee.pRiver.0.0-0.0.0.pGround	0.38	98%
Combined	Intercept	pLevee.pRiver.0.0-0.pRiver.0.pGround	0.28	94%
Combined	Intercept	pLevee.pRiver.0.0-pLevee.pRiver.0.pGround	0.29	93%
Combined	Intercept	pLevee.pRiver.0.0-0.0.pSurface.pGround	0.37	97%
Combined	Intercept	0.0.pSurface.0-0.pRiver.pSurface.0	-0.23	4%
Combined	Intercept	0.0.pSurface.0-pLevee.pRiver.pSurface.0	-0.3	4%
Combined	Intercept	0.0.pSurface.0-0.pRiver.pSurface.pGround	-0.23	6%
Combined	Intercept	0.pRiver.pSurface.0-0.0.0.pGround	0.21	91%

Pairs of coefficients with 90% credible differences within each model variant (continued)

Model variant	Variable	Difference in flood pathways estimates	Median of difference	Fraction of distribution beyond zero
Combined	Intercept	pLevee.pRiver.pSurface.0-0.0.0.pGround	0.28	93%
Combined	Intercept	pLevee.pRiver.pSurface.0-0.0.pSurface.pGround	0.27	90%
Combined	WaterDepth	pLevee.0.0.0-0.0.pSurface.0	0.28	>99.5%
Combined	WaterDepth	pLevee.0.0.0-0.pRiver.pSurface.0	0.14	90%
Combined	WaterDepth	pLevee.0.0.0-0.pRiver.0.pGround	0.19	95%
Combined	WaterDepth	0.pRiver.0.0-0.0.pSurface.0	0.25	>99.5%
Combined	WaterDepth	0.pRiver.0.0-0.pRiver.0.pGround	0.16	94%
Combined	WaterDepth	0.0.pSurface.0-0.pRiver.pSurface.0	-0.14	7%
Combined	WaterDepth	0.0.pSurface.0-pLevee.pRiver.pSurface.0	-0.19	8%
Combined	WaterDepth	0.0.pSurface.0-0.0.0.pGround	-0.22	3%
Combined	WaterDepth	0.0.pSurface.0-0.0.pSurface.pGround	-0.19	5%
Combined	WaterDepth	0.0.pSurface.0-0.pRiver.pSurface.pGround	-0.23	1%
Combined	Contamination	pLevee.0.0.0-0.pRiver.0.0	0.11	90%