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PLUVIAL FLOOD LOSS TO PRIVATE HOUSEHOLDS

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"Nothing in life is to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less."

– Maria Skłodowska-Curie

Declaration of originality

Potsdam, May 9, 2019

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

Viktor Rözer

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Zusammenfassung

Über die Hälfte der Weltbevölkerung lebt heute in Städten. Mit einer hohen Dichte an Menschen, Gütern und Gebäuden sind Städte nicht nur die wirtschaftlichen, politischen und kulturellen Zentren einer Gesellschaft, sondern auch besonders anfällig gegenüber Naturkatastrophen. Insbesondere Hochwasser und Überflutungen stellen in Folge von steigenden Meeresspiegeln und einer erwarteten Zunahme von Extremwettereignissen eine wachsende Bedrohung in vielen Regionen dar.

Um die möglichen Folgen dieser Entwicklung zu vermeiden bzw. zu reduzieren, ist es notwendig sich der steigenden Gefahr durch geeignete Maßnahmen anzupassen. Bisher ist der Hochwasserschutz in Städten beinahe ausschließlich auf Überflutungen durch Flusshochwasser oder Sturmfluten fokussiert. Dabei werden sogenannte urbane Sturzfluten, die in den letzten Jahren vermehrt zu hohen Schäden in Städten geführt haben, nicht berücksichtigt. Bei urbanen Sturzfluten führen lokale Starkniederschläge mit hohen Regenmengen zu einer Überlastung des städtischen Abwassersystems und damit zu einer direkten, oft kleinräumigen Überflutung innerhalb eines bebauten Gebiets. Mit einer prognostizierten Zunahme von Starkniederschlägen, sowie einer baulichen Verdichtung und damit einhergehender Flächenversiegelung in vielen Städten, ist mit einer Zunahme von urbanen Sturzfluten zu rechnen. Dies verlangt die Einbindung des Risikos durch urbane Sturzfluten in bestehende Hochwasserschutzkonzepte. Bisher fehlen allerdings sowohl detaillierte Daten als auch Methoden um das Risiko durch urbane Sturzfluten und die dadurch verursachten Schäden, etwa an Wohngebäuden, zuverlässig abzuschätzen.

Aus diesem Grund beschäftigt sich diese Arbeit hauptsächlich mit der Entwicklung von Verfahren und Modellen zur Abschätzung von Schäden an Privathaushalten durch urbane Sturzfluten. Dazu wurden detaillierte Daten durch Telefon- und Online-Umfragen nach urbanen Sturzflutereignissen in Deutschland und in den Niederlanden erhoben und ausgewertet. Die Erkenntnisse aus den detaillierten Analysen zu Vorsorge, Notmaßnahmen und Wiederherstellung, vor, während und nach urbanen Sturzflutereignissen, wurden genutzt um eine neue Methode zur Schätzung von Schäden an Wohngebäuden zu entwickeln. Dabei werden neben Angaben wie Dauer und Höhe der Überflutung, auch Eigenschaften von Haushalten, wie etwa deren Risikobewusstsein, in die Schätzung miteinbezogen. Nach lokaler Validierung wurde die neuentwickelte Methode beispielhaft zur Schätzung von Wohngebäudeschäden nach einem urbanen Sturzflutereignis im Großraum Houston (Texas, USA) erfolgreich angewendet. Anders als bei bisherigen Ansätzen wird der geschätzte Schaden eines Wohngebäudes nicht als einzelner Wert angegeben, sondern als Verteilung, welche die Bandbreite möglicher Schäden und deren Wahrscheinlichkeit angibt. Damit konnte die Zuverlässigkeit von Schadensschätzungen im Vergleich zu bisherigen Verfahren erheblich verbessert werden. Durch die erfolgreiche Anwendung sowohl auf der Ebene einzelner Gebäude als auch für gesamte Städte, ergibt sich ein breites Spektrum an Nutzungsmöglichkeiten, etwa als Entscheidungsunterstützung in der Stadtplanung oder für eine verbesserte Frühwarnung vor urbanen Sturzfluten.

Summary

Today, more than half of the world's population lives in urban areas. With a high density of population and assets, urban areas are not only the economic, cultural and social hubs of every society, they are also highly susceptible to natural disasters. As a consequence of rising sea levels and an expected increase in extreme weather events caused by a changing climate in combination with growing cities, flooding is an increasing threat to many urban agglomerations around the globe.

To mitigate the destructive consequences of flooding, appropriate risk management and adaptation strategies are required. So far, flood risk management in urban areas is almost exclusively focused on managing river and coastal flooding. Often overlooked is the risk from small-scale rainfall-triggered flooding, where the rainfall intensity of rainstorms exceeds the capacity of urban drainage systems, leading to immediate flooding. Referred to as pluvial flooding, this flood type exclusive to urban areas has caused severe losses in cities around the world. Without further intervention, losses from pluvial flooding are expected to increase in many urban areas due to an increase of impervious surfaces compounded with an aging drainage infrastructure and a projected increase in heavy precipitation events. While this requires the integration of pluvial flood risk into risk management plans, so far little is known about the adverse consequences of pluvial flooding due to a lack of both detailed data sets and studies on pluvial flood impacts. As a consequence, methods for reliably estimating pluvial flood losses, needed for pluvial flood risk assessment, are still missing.

Therefore, this thesis investigates how pluvial flood losses to private households can be reliably estimated, based on an improved understanding of the drivers of pluvial flood loss. For this purpose, detailed data from pluvial flood-affected households was collected through structured telephone- and web-surveys following pluvial flood events in Germany and the Netherlands.

Pluvial flood losses to households are the result of complex interactions between impact characteristics such as the water depth and a household's resistance as determined by its risk awareness, preparedness, emergency response, building properties and other influencing factors. Both exploratory analysis and machine-learning approaches were used to analyze differences in resistance and impacts between households and their effects on the resulting losses. The comparison of case studies showed that the awareness around pluvial flooding among private households is quite low. Low awareness not only challenges the effective dissemination of early warnings, but was also found to influence the implementation of private precautionary measures. The latter were predominately implemented by households with previous experience of pluvial flooding. Even cases where previous flood events affected a different part of the same city did not lead to an increase in preparedness of the surveyed households, highlighting the need to account for small-scale variability in both impact and resistance parameters when assessing pluvial flood risk.

While it was concluded that the combination of low awareness, ineffective early warning and the fact that only a minority of buildings were adapted to pluvial flooding impaired the coping capacities of private households, the often low water levels still enabled households to

mitigate or even prevent losses through a timely and effective emergency response.

These findings were confirmed by the detection of loss-influencing variables, showing that cases in which households were able to prevent any loss to the building structure are predominately explained by resistance variables such as the household's risk awareness, while the degree of loss is mainly explained by impact variables.

Based on the important loss-influencing variables detected, different flood loss models were developed. Similar to flood loss models for river floods, the empirical data from the preceding data collection was used to train flood loss models describing the relationship between impact and resistance parameters and the resulting loss to building structures. Different approaches were adapted from river flood loss models using both models with the water depth as only predictor for building structure loss and models incorporating additional variables from the preceding variable detection routine.

The high predictive errors of all compared models showed that point predictions are not suitable for estimating losses on the building level, as they severely impair the reliability of the estimates. For that reason, a new probabilistic framework based on Bayesian inference was introduced that is able to provide predictive distributions instead of single loss estimates. These distributions not only give a range of probable losses, they also provide information on how likely a specific loss value is, representing the uncertainty in the loss estimate.

Using probabilistic loss models, it was found that the certainty and reliability of a loss estimate on the building level is not only determined by the use of additional predictors as shown in previous studies, but also by the choice of response distribution defining the shape of the predictive distribution. Here, a mix between a beta and a Bernoulli distribution to account for households that are able to prevent losses to their building's structure was found to provide significantly more certain and reliable estimates than previous approaches using Gaussian or non-parametric response distributions.

The successful model transfer and post-event application to estimate building structure loss in Houston, TX, caused by pluvial flooding during Hurricane Harvey confirmed previous findings, and demonstrated the potential of the newly developed multi-variable beta model for future risk assessments. The highly detailed input data set constructed from openly available data sources containing over 304,000 affected buildings in Harris County further showed the potential of data-driven, building-level loss models for pluvial flood risk assessment.

In conclusion, pluvial flood losses to private households are the result of complex interactions between impact and resistance variables, which should be represented in loss models. The local occurrence of pluvial floods requires loss estimates on high spatial resolutions, i.e. on the building level, where losses are variable and uncertainties are high.

Therefore, probabilistic loss estimates describing the uncertainty of the estimate should be used instead of point predictions. While the performance of probabilistic models on the building level are mainly driven by the choice of response distribution, multi-variable models are recommended for two reasons:

First, additional resistance variables improve the detection of cases in which households were able to prevent structural losses.

Second, the added variability of additional predictors provides a better representation of the uncertainties when loss estimates from multiple buildings are aggregated.

This leads to the conclusion that data-driven probabilistic loss models on the building level allow for a reliable loss estimation at an unprecedented level of detail, with a consistent quantification of uncertainties on all aggregation levels. This makes the presented approach suitable for a wide range of applications, from decision support in spatial planning to impact-based early warning systems.

Contents

Glossary

Bayesian inference
Statistical inference method using Bayes' theorem to update the probability of a hypothesis when more evidence or data becomes available.

beta distribution
A family of continuous statistical distributions defined on the interval [0, 1].

Bernoulli distribution
Discrete probability distribution describing the probability of a random variable to be 0 or 1.

building content
Portable or semi-permanently attached goods inside or attached to a building.

building structure
Permanent and/or non-removable parts of a building.

extreme rainfall
Short-duration, high intensity rainfall that can cause damage to buildings both by direct penetration through roofs or walls or by leading to *pluvial flooding*.

flood impact
Damaging properties of flooding determined by factors such as the depth, duration and contamination of the floodwater.

flood loss and flood damage
Temporary or permanent physical harm caused by the effects of flooding. The terms 'loss' and 'damage' are used synonymously in this thesis.

flood resistance
The ability of an object or individual to be not or less affected by the adverse consequences of flooding.

flood risk management
Management approach that aims to reduce the likelihood and/or the impact of floods through prevention, protection, preparedness and emergency response as well as to facilitate the recovery after a flood event.

fluvial flooding
See *river flooding*.

loss model
: Mathematical model that quantifies the monetary losses associated with a natural disaster or a comparable event.

machine learning
: Predictive modeling technique that uses statistical methods to give computer systems the ability to autonomously improve model predictions using data.

pluvial flooding
: Flooding directly caused by rain storms over urban areas when precipitation intensities exceed the capacity of the natural and engineered drainage systems in urban areas. Flooding is independent from overflowing water bodies.

probabilistic model
: Mathematical model with multiple possible outcomes, each representing varying degrees of certainty of its occurrence.

reliability
: Ability of a probabilistic model to produce prediction intervals that contain the observed value.

river flooding
: The rise of the water level of a river to an elevation such that the river overflows its natural or built banks.

sharpness
: The concentration of the predictive distribution from a predictive model. The higher the sharpness and reliability of a predictive distribution, the better the prediction.

stage-damage function
: Function describing the relationship between flood losses and the inundation depth of a flood. Stage-damage functions are typically developed for a specific building class or land use based on data from previous events (empirical) or what-if analysis (synthetic).

variable importance
: Measure in a predictive model referring to the ability of a variable to improve the prediction. The importance of a variable increases, the more a model relies on this variable to make predictions.

zero-loss case
: Cases in which flood water has entered a building but did not cause any monetary loss or damage to the building structure or content.

Abbreviations

ACS	American Community Survey
CATI	Computer-Aided Telephone Interview
CC	Creative Commons
DWD	Deutscher Wetterdienst (German Weather Service)
EU	European Union
EUR	Euro (currency)
FEMA	Federal Emergency Management Agency
G2G	Grid-to-grid
GDV	Gesamtverband der Deutschen Versicherungswirtschaft (German Insurer Association)
GIS	Geographic Information System
HCAD	Harris County Appraisal District
HDI	Highest Density Interval
HR	Hit Rate
IS	Interval Score
KMNI	Koninklijk Nederlands Meteorologisch Instituut (Royal Netherlands Meteorological Institute)
LANUV NRW	Landesamt für Natur, Umwelt und Verbraucherschutz Nordrhein-Westfalen (North Rhine-Westphalia State Environmental Agency)
MCMC	Markov Chain Monte Carlo
MBE	Mean Bias Error
NRC	National Response Center
NUTS	No U-Turn Sampler
PNNL	Pacific Northwest National Laboratory
SDF	Stage-Damage Function
SMS	Short Message Service

THW	Technisches Hilfswerk (Federal Agency for Technical Relief)
TX	Texas
UK	United Kingdom
USA	United States of America
USD	US Dollar (currency)
UTC	Coordinated Universal Time
RCNLD	Replacement Cost New Less Depreciation
RMSE	Root Mean Squared Error
ZKI	Zentrum für satellitengestützte Kriseninformation (Center for Satellite-based Crisis Information)

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1 Motivation and objectives

1.1 Flooding in urban areas

In 2008, the Department of Economic and Social Affairs of the United Nations announced that half of the world's population were currently living in urban settlements, and a recent update estimates that the share of urban dwellers will reach two-thirds by 2050 (UN DESA, 2008, 2018). While at first glance this information has little to do with natural disasters, ongoing urbanization has far-reaching implications for the global natural disaster risk. With a high concentration of population and assets, urban areas are not only the economic, cultural and social hubs of every society, but are also highly susceptible to natural disasters (IMECHE, 2013).

Of the estimated USD 4.3 trillion lost and 1.7 million people killed by natural disasters between 1980 and 2016, a substantial amount occurred in urban areas (Munich Re, 2018; Gu et al., 2015). Based on the occurrence of historical losses between 1981 and 2000, 88% of cities worldwide with over 300,000 inhabitants were found to be highly vulnerable to economic losses and 82% were found to be exposed to a high mortality vulnerability from at least one type of natural disaster. Among the different types of natural disasters, floods are the most common in terms of both fatalities and direct economic losses and are also the most common natural disaster in urban areas, with 71% of cities worldwide being located in areas with a high vulnerability to flood related economic losses (Gu et al., 2015; Doocy et al., 2013).

Descriptions and categorizations of floods can vary, but are commonly based on a combination of sources, causes and spatial scales as well as onset time and duration (Kron, 2005; Jha et al., 2012). Based on these combinations four main types of flooding can be distinguished: storm surges or coastal floods, where waves move inland due to a combination of low pressure areas, high wind speeds and high tide; river (or fluvial) floods, where the water level of rivers raise to an elevation such that the river overflows its banks; ground water floods, where a rise in the groundwater table floods lower-lying structures; and rainfall-triggered overland floods, where the precipitation intensity of local rainstorms is higher than the infiltration capacity of the ground, leading to flooding before the water reaches a larger watercourse. Depending on the onset time of flooding, floods are often further differentiated into flash floods and slowly rising floods.

In urban areas, flooding is the result of a complex interaction between the previously described natural processes and the built environment, and are therefore often caused or intensified by a failure of flood defense measures, drainage infrastructure or other anthropogenic causes (Dawson et al., 2008) (see Table 1.1).

Here, the extensive sealing of absorptive land cover with impervious surfaces leads to a special case of rainfall-triggered flooding exclusive to urban areas: In the case of short-duration rain storms over urban areas, where precipitation intensities exceed the design levels of the urban drainage system, the water remains on impermeable surfaces or flows into local depressions, leading to an almost immediate flooding of streets and buildings (Houston et al., 2011) (see Figure 1.1).

Table 1.1: Flood types in urban areas (adapted and modified from Jha et al. (2012))

Flood type	**Natural cause**	**Anthropogenic cause (examples)**	**Onset time**
Pluvial	Rainstorm	Capacity of sewage system exceeded Poorly managed/faulty drainage system Lack of permeable surfaces due to increased urban concentration	Rapid
Fluvial	River overflow	Development in flood plains Failure of structural flood defense (levees) Failure in dam management	Usually slow Rapid in case of levee breaches
Ground water	Rise in ground-water level	Development in low lying areas Lower water abstraction from wells, due to decreasing water consumption	Slow
Coastal	Storm surge	Development in coastal zones Removal of natural flood barriers (mangroves, dunes)	Fairly rapid Rapid in case of dike breaches

This type of flooding is of central importance in this thesis and is referred to in the remainder of the thesis as *pluvial flooding*[1].

As drainage systems in densely populated urban areas are typically designed to convey runoff from rain storms with a duration and intensity corresponding to statistical return periods between 2 and 10 years[2] (so called *design storms*) (ASCE, 2006; Guo, 2006; Ten Veldhuis, 2011; Rosenzweig et al., 2018), pluvial floods are common, yet often gain less attention than river or coastal floods as their impacts are mostly local.

However, recent pluvial flood events in different regions around the world have demonstrated the serious consequences of pluvial flooding. Well-documented examples include a severe rainstorm with 150 mm of rainfall within three hours that hit the city of Copenhagen in July 2011 causing estimated flood losses of over USD 1 billion (DKK 6.2 billion), or the pluvial flood in Beijing in July 2012 with rainfall rates varying between 100 mm and 460 mm over a period of 20 hours affecting large parts of the city, killing 79 people and causing estimated losses of over USD 1.86 billion (CNY 11.6 billion)(Wojcik et al., 2013; Wang et al., 2013). Pluvial flooding in the Houston, TX, area caused by record-setting rainfall during Hurricane Harvey in August 2017 was also responsible for the largest share of the estimated USD 125 billion in total losses and 36 fatalities (Jonkman et al., 2018; NOAA, 2018).

Besides individual high-impact events, a considerable part of the cumulative pluvial flood losses over time is caused by frequent small-scale flooding exceeding those of rare, high-impact events in many areas. For the case of pluvial flooding in the Netherlands, it is estimated that the cumulative pluvial flood loss of 10 years of successive flood events is similar to the loss of a single pluvial flood event with an estimated return period of 125 years (Ten Veldhuis, 2011). For Germany Einfalt et al. (2009) estimates that the sum of losses from small pluvial flood events account for several million Euros per year.

In addition to ongoing urbanization with further concentration of population and wealth in urban areas, weather- and climate related impacts as a consequence of a changing climate have been identified as important drivers of future disaster risk in cities (Hunt and Watkiss, 2011). While these impacts include the well-studied effect of sea level rise on coastal cities

[1]Other terms frequently mentioned in the literature include *surface water flooding, urban pluvial flooding, urban flooding, urban water logging and urban flash floods.*

[2]For comparison: Protection standards used in the floodplain management of river floods are typically based on return periods in the range of 100 to 500 years (Gersonius et al., 2012; Rosenzweig et al., 2018).

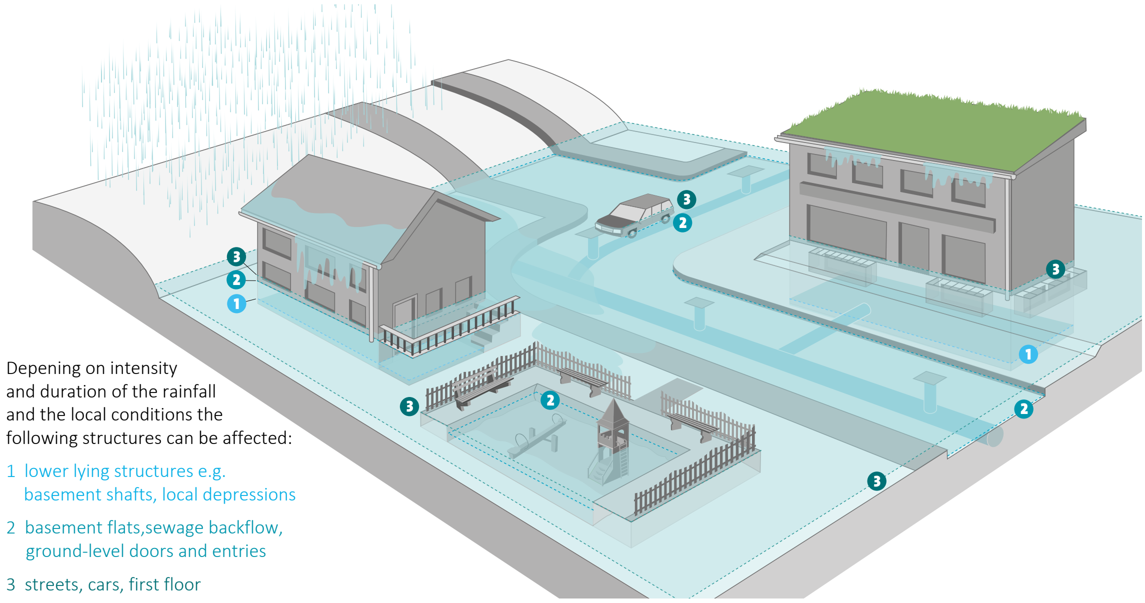

Figure 1.1: Affected structures during a pluvial flood (from GDV (2015); adapted).

(Nicholls and Cazenave, 2010; Hinkel et al., 2014), the projected increase in pluvial flooding due to an increase in frequency and intensity of heavy rainfall events in many areas around the globe (Kundzewicz et al., 2014; Field et al., 2012) including Germany (Bronstert et al., 2017) has gained far less attention. However, pluvial flooding is expected to increase the disaster risk not only in urban areas that lie in coastal or river flood plains, but also in areas that have not been considered flood-prone. Hence, it is important to consider pluvial flood risk when assessing the current and future flood risk in urban areas for the purposes of risk management and adaptation planning.

1.2 The need to better understand pluvial flood risk

Until recently, pluvial flooding has received only limited attention in flood risk research, planning and policy. There are several reasons for this, including (i) the assumption that existing design and operation standards of urban drainage systems are sufficient to prevent the majority of pluvial flood events when properly managed (Fletcher et al., 2015; Cherqui et al., 2015), (ii) the underestimation of pluvial flood risk as nuisance with minimal impacts (Ten Veldhuis and Clemens, 2010), and (iii) the lack of information on the occurrence of rainstorms that cause pluvial flooding due to the small spatial and temporal scales of these storm events (Rosenzweig et al., 2018).

However, with an increased sealing of surfaces and further densification in many urban areas together with an expected increase in heavy precipitation events, the need to integrate pluvial flooding into urban flood risk management is increasingly recognized (Zevenbergen et al., 2008; Willems et al., 2012; Jiang et al., 2018).

Following the widely used definition for natural disaster risk, pluvial flood risk can be understood as a function of *hazard, exposure* and *vulnerability*, where the *hazard* refers to the probability of a flood event occurring with a specific intensity, the *exposure* refers to the number of people and assets impacted by the event, and the *vulnerability* refers to the severity of impacts experienced by the exposed population and assets (Cutter, 1996; Kron, 2005).

So far, a considerable number of studies on pluvial flooding, have focused on improving the understanding of pluvial flood hazard and exposure, including studies on how changing precipitation patterns affect the occurrence and intensity of pluvial flood events as well as the delineation of flooded areas (Arnbjerg-Nielsen et al., 2013; Blanc et al., 2012; Ghimire et al., 2013). The latter is also supported by an increasing number of urban drainage models available for flood inundation modeling (Bach et al., 2014; Salvadore et al., 2015).

However, only a few studies investigate the vulnerability of inhabitants and assets to pluvial flooding. Among the exceptions are studies by Houston et al. (2011) and Douglas et al. (2010), who investigate the consequences and impacts of two subsequent pluvial flood events in the UK, as well as Van Ootegem et al. (2015) and Spekkers et al. (2014), who analyze the effect of different hazard and non-hazard variables on pluvial flood losses.

Although these studies confirm that the vulnerability of population and assets plays an important role in pluvial flood risk, they also conclude that the processes influencing the impacts of pluvial flooding are still poorly understood. This lack of understanding includes how human behavior before, during and after a flood influences the risk of flooding (Aerts et al., 2018). Here, stronger links between physical and social dimensions are expected to support a more comprehensive understanding of pluvial flood vulnerability (Cho and Chang, 2017).

Therefore, closing knowledge gaps around how urban dwellers cope with pluvial flooding and how this affects the impact is important for the development of comprehensive risk management and mitigation strategies. One key limitation in the analysis of impacts and factors influencing the vulnerability to pluvial flooding is the availability of suitable data (Hammond et al., 2015). Previous studies on pluvial flood vulnerability and impacts have identified several shortcomings in the available data sources.

This includes claims data from insurance data bases that often do not allow a distinction to be made between different water-related losses and have only a limited amount of additional information due to privacy regulations (Spekkers et al., 2013; Grahn and Nyberg, 2017), or call records of reported incidents from municipal call centers, which are often incomplete and lack detailed information on the incident (Ten Veldhuis and Clemens, 2010). From an analysis of historic pluvial flood events, Smith and Lawson (2012) find a bias in the frequency of news reports due to a growing media interest in climate-change related impacts. Self-reported information from web, postal or telephone surveys of households affected by pluvial flooding are expected to be able to overcome this lack of detailed information on the impacts and associated parameters, but these are so far limited to a few additional variables for individual events(Van Ootegem et al., 2015).

This underlines the importance of collecting and analyzing detailed information on pluvial flood impacts and associated parameters to not only improve the understanding of vulnerability in pluvial flood risk, but also to support a comprehensive assessment of urban flood risk.

1.3 Pluvial flood loss models

Flood losses in urban areas both from individual events and over time can be significant. They include direct financial losses due to damage to the building envelope, building contents and the city's infrastructure, as well as indirect financial losses, such as business and supply chain interruptions (Haraguchi and Lall, 2015). However, also impacts that are difficult to quantify play a role, such as consequences on the mental and physical health of affected residents (Tapsell and Tunstall, 2008; Fewtrell and Kay, 2008).

Flood loss models quantify the financial impacts in monetary terms, aiding the development of cost-efficient risk reduction strategies, and are therefore an important component of an integrated flood risk management (Merz et al., 2010; Hammond et al., 2015). They are usually separated by sector (i.e. residential buildings, infrastructure, businesses) and flood type (see Table 1.1). The majority of available flood loss models focus on direct losses to the residential sector caused by river or coastal flooding (Gerl et al., 2016). Loss models for pluvial floods have not been developed to the same extent due to a lack of data on the impacts as well as lacking or uncertain information on the flooding itself (Freni et al., 2010; Olsen et al., 2015).

For the quantification of direct economic losses in urban areas, stage-damage functions (SDF), that describe the relationship between water level and relative or absolute economic losses for different buildings and sectors are the internationally accepted standard (Grigg and Helweg, 1975; Smith, 1994; Gerl et al., 2016). These functions are either derived from empirical loss information collected after flood events or from synthetic approaches based on hypothetical assumptions about the expected loss for a given water depth (Merz et al., 2010). Although SDFs are the most widely used type of loss model, the uncertainties in loss estimates are high, reflecting the lack of understanding about the damaging processes, natural variability and the underlying uncertainty around input parameters, which are often estimates themselves (i.e. estimated or modeled water depth in- or outside of a building) (Merz et al., 2004; Freni et al., 2010).

With a higher level of detail in the analysis, the uncertainties of loss estimates from SDFs increase, making loss estimates on the level of individual buildings or building blocks highly uncertain (Merz et al., 2004; Scawthorn et al., 2006; Tate et al., 2014). This challenges the reliable estimation of losses from pluvial floods as the majority of pluvial flood events occur on the scale of a few houses to individual neighborhoods within a city.

Apart from unit cost methods, where a pre-defined loss value is allocated to a building when the (modeled) flood depth exceeds a certain threshold (Zhou et al., 2012; Sušnik et al., 2015; Olsen et al., 2015), previous attempts to estimate pluvial flood losses have used two different approaches: adapting existing SDFs from river or coastal flooding (Freni et al., 2010), as well as relating rainfall intensities and duration to pluvial flood losses. While the latter circumvents the often high uncertainties in water level inputs from urban drainage models, the available information on rainfall intensity and duration from radar and gauge measurements alone are not sufficient to explain the variability in losses (Climate Service Center, 2013; Spekkers et al., 2014; Van Ootegem et al., 2018). Both approaches using rainfall-loss and water-depth-loss relationships build on recent developments in loss models for other flood types. This includes the use of additional predictors as well as different model types, such as tree-based models (Spekkers et al., 2014) or multivariate regression models (Van Ootegem et al., 2015).

Although previous loss models for pluvial floods have provided important information on the influence of different non-hazard variables, so far little is known whether these approaches are also suitable for predicting pluvial flood losses. However, approaches to reliably estimate and predict pluvial flood losses are necessary to include pluvial flood risk into urban flood risk management strategies. Therefore, the development and improvement of pluvial flood loss estimation models is an important step for a comprehensive management of the urban flood risk.

1.4 Objective, research questions and outline

Pluvial flooding is an increasing risk in many urban areas around the world, but has received only limited attention in urban flood risk assessment to date. The lack of data and limited understanding of the damaging processes has so far hindered a reliable estimation of direct financial losses from pluvial flooding.

However, the reliable quantification of losses from pluvial floods is necessary for a comprehensive integrated flood risk management including cost-benefit analysis of disaster risk reduction measures. While in urban areas different sectors and land use types including businesses, industry and infrastructure can be affected by pluvial flooding, both the assessment of their risk and the quantification of the losses require very different approaches and data sets. As the comprehensive analysis and model development for each of the different sectors and land use types in urban areas would exceed the scope of this thesis, the subsequent chapters focus on the private household sector.

Therefore, the main objective of this thesis is to **improve the estimation of pluvial flood losses** to private households through an **improved understanding of the loss-influencing factors** and the **underlying uncertainties**, based on **statistical analysis of empirical data** from flood affected households, with the overarching aim of providing methods that can support decisions on how to manage pluvial flood risk in urban areas. This results in five research questions, addressed in the chapters denoted in brackets:

1. How do private households cope with pluvial flooding? (Chapters 2 and 3)
2. What explains the differences in preparedness and response between households affected by pluvial flooding? (Chapters 2 and 3)
3. Which factors influence pluvial flood losses to private households? (Chapters 2, 3 and 4)
4. Can implementing these factors in loss models improve the quantification of pluvial flood losses? (Chapter 4)
5. What influences the reliability and uncertainty of pluvial flood loss models (Chapter 4)?

The structure of this cumulative thesis consists of an introductory chapter and three main chapters, addressing the main research questions, and a concluding chapter discussing the main findings of this thesis within a broader context. Chapters 2 to 4 of this thesis take the form of manuscripts that have been published in peer-reviewed journals or are currently under review for publication. While each of the three main chapters addresses specific research questions, they are arranged to follow a four-step study design consisting of data collection, data analysis, model development and model application (see Figure 1.2).

Chapters 2 and 3 describe the collection and analysis of data from past pluvial flood events. Chapter 2 analyzes how private households prepare for, respond to and recover from pluvial flooding based on detailed survey data from three pluvial flood events in three different German cities in 2005 and 2010. Chapter 3 analyzes regional differences in preparedness and response between two pluvial flood events in Germany and the Netherlands. Chapter 3 further discusses different data collection strategies for pluvial flood loss data.

Chapter 4 derives potentially loss-influencing variables based on data and findings from the previous chapters. Machine learning and data mining approaches are used to systematically screen the variables for their potential to improve loss estimates before implementing the most important loss influencing variables in a newly developed, probabilistic, multi-variable loss estimation model. The loss estimation model is validated, compared with other probabilistic loss models, and applied to estimate the uncertainties in building structure loss to private households during a recent pluvial flood event.

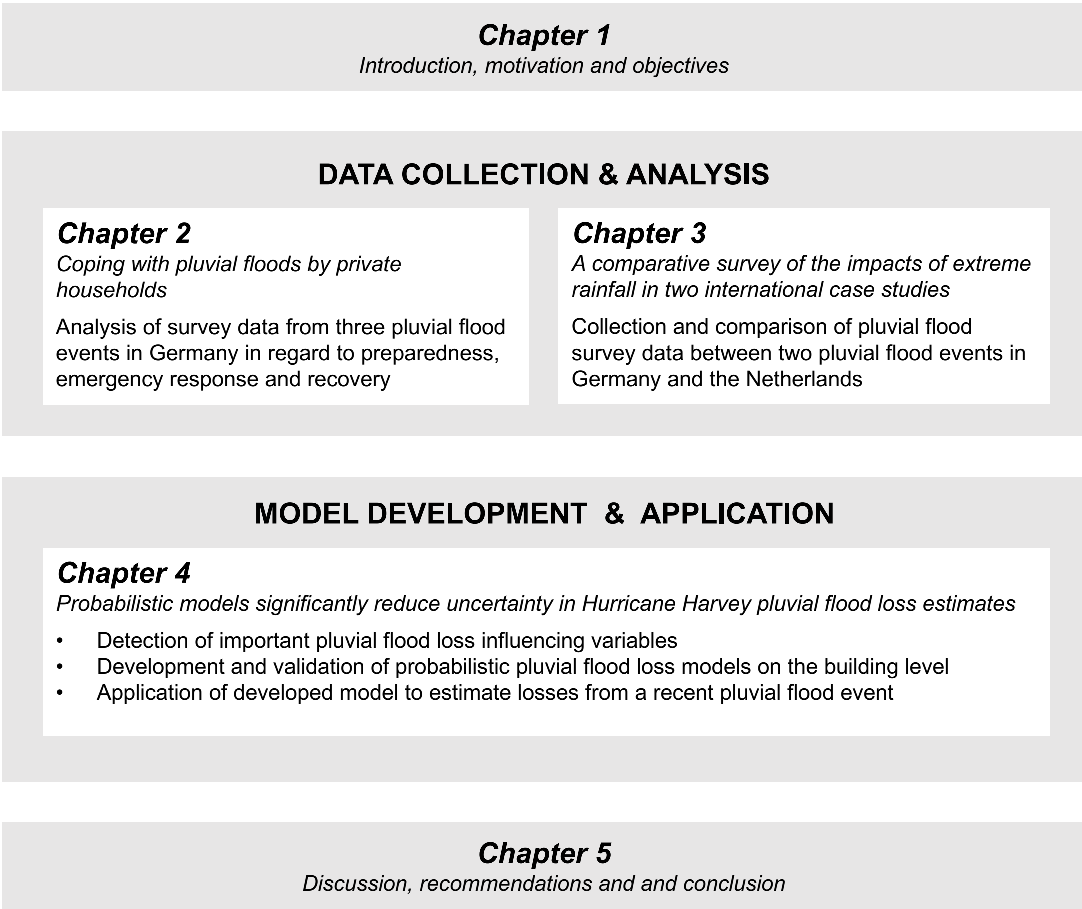

Figure 1.2: Structure of the thesis.

1.5 Author contributions

The manuscripts in the following three chapters are the result of a collaboration between the author of this thesis (V.R.) and several co-authors. In the following, the contributions of V.R. and all co-authors (initials) are outlined for each manuscript:

Chapter 2: Coping with pluvial floods by private households

V.R. and H.K. designed the research with contributions from A.T.; V.R. analyzed the data for Sections 2.3.2 to 2.4.3, interpreted the results, generated all figures and tables in this paper, wrote Sections 2.3.2 to 2.4.3 and Section 2.5 and was responsible for writing the paper; M.M. and O.B. designed and conducted the survey of flood-affected households in Hersbruck and Lohmar; M.M. wrote Sections 2.2.1 and 2.2.2; A.T., H.K. and M.M. designed and conducted the survey of flood-affected households in Osnabrück; H.K. wrote Section 2.1, contributed to Section 2.5 and contributed to the interpretation of the results; A.T. wrote Section 2.2.3; P.B. performed all analysis in Section 2.4.4, as well as wrote Section 2.4.4; S.K. wrote Section 2.3.1; K.S. contributed to Sections 2.1 and 2.5 and contributed to the interpretation of the results; I.P. prepared the survey data used in this analysis and contributed to Section 2.3.1.

Chapter 3: A comparative survey of the impacts of extreme rainfall in two international case studies

V.R. and M.S. designed the research with support from H.K. M.-C.V. and A.T.; V.R. and M.S. were responsible for writing the paper; V.R. and M.S. generated all figures and tables; V.R. collected the data in Münster with support from H.K. and A.T.; M.S. collected the data in Amsterdam with support from M.-C.V.; V.R. and M.S. performed the data analysis (Section 3.3) and interpreted the results (Section 3.4) with support from H.K. and M.-C.V. and inputs from A.T.; V.R. wrote Sections 3.2.1, 3.2.3 and 3.4 with contributions from M.S. ; M.S. wrote Sections 3.2.2, 3.3 and 3.5 with contributions from V.R.; M.S. compiled the supporting information (Section 3.A) with contributions from V.R.; A.K. and H.K. wrote Section 3.1 with contributions from V.R. and M.S.

Chapter 4: Probabilistic models significantly reduce uncertainty in Hurricane Harvey pluvial flood loss estimates

V.R. designed the research, performed the data analysis, developed the models, interpreted the results, generated all figures and tables (except for Figure 4.5 and Table 4.3) and wrote the paper; H.K., K.S., U.L. and B.M. contributed to the design of the research and the interpretation of the results; H.K. wrote Section 4.A.1 – *Survey data* and generated Table 4.3.; K.S., J.D.-G. and N.S. contributed to the model development and validation; M.M. contributed to the data collection and processing of the survey data of flood-affected households in Germany; N.S. wrote Section 4.A.2 - *Probabilistic multi-variate beta model* and generated Figure 4.5; V.R. compiled the supporting information (Section 4.A).

2 Coping with pluvial floods by private households

Summary. Pluvial floods have caused severe damage to urban areas in recent years. With a projected increase in extreme precipitation as well as an ongoing urbanization, pluvial flood damage is expected to increase in the future. Therefore, further insights, especially on the adverse consequences of pluvial floods and their mitigation, are needed. To gain more knowledge, empirical damage data from three different pluvial flood events in Germany were collected through computer-aided telephone interviews. Pluvial flood awareness as well as flood experience were found to be low before the respective flood events. The level of private precaution increased considerably after all events, but is mainly focused on measures that are easy to implement. Lower inundation depths, smaller potential losses as compared with fluvial floods, as well as the fact that pluvial flooding may occur everywhere, are expected to cause a shift in damage mitigation from precaution to emergency response. However, an effective implementation of emergency measures was constrained by a low dissemination of early warnings in the study areas. Further improvements of early warning systems including dissemination as well as a rise in pluvial flood preparedness are important to reduce future pluvial flood damage.

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2.1 Introduction

Pluvial floods in urban areas are caused by storm events with exceptionally high rainfall rates, which lead to inundation of streets and buildings. Commonly, failure of the drainage system plays an important role. Often referred to as surface water flooding, many European cities experienced pluvial flooding in recent years, which caused considerable damage. Examples are the pluvial flood in the City of Hull in the UK in 2007, where more than 100 mm of rain over a 24 h period caused damage to 8600 residential buildings and 1300 businesses (Coulthard and Frostick, 2010) and the pluvial flood in the city of Dortmund, Germany, in July 2008, where local rainfall rates of 200 mm over a time span of 3 h led to a total loss of Euro (EUR) 17.2 million (Grünewald et al., 2009). Pluvial flood risk is expected to increase in the future. Due to climate change, it is expected that the frequency and intensity of heavy rainfall events increases, which should contribute to increases in precipitation-generated local flooding (Kundzewicz et al., 2014). However, increasing exposure and vulnerability of cities also play a role (Semadeni-Davies et al., 2008; Kaspersen et al., 2015). Thus, for pluvial flooding, an efficient, integrated risk management following the risk management cycle is also necessary (Kreibich et al., 2014; Sušnik et al., 2015). However, pluvial floods often occur at much smaller spatial and temporal scales than fluvial floods. They may occur anywhere, including in areas not obviously prone to flooding, which has important implications in terms of experience and preparedness of the population. Since pluvial floods are often related to convective storms, they have a high spatial and temporal dynamic, which challenges early warning systems (DKKV, 2015). As a result, lead times are short, i.e. only up to a few hours are available for undertaking response measures. While risk management and mitigation strategies for fluvial and tidal floods have been established over the last decades, effective strategies to face an increasing pluvial flood risk, were not developed to the same extent (Zhou et al., 2012; Hammond et al., 2015; Penning-Rowsell et al., 2010).

Case studies have shown that suitable risk reduction for pluvial flooding, which consists of preventive, protective and preparative measures, can be difficult to achieve. For instance, a case study in the city of Eindhoven in the Netherlands revealed that pluvial flood protection via a separation of sewer and storm water networks and an increase of urban water storage has a negative cost-benefit ratio (Sušnik et al., 2015). Another study in the Greater Manchester area in the UK investigating pluvial flood events in 2004 and 2006 showed that the affected people were not well informed or prepared and even confused about the responsibilities before, during and after the events (Douglas et al., 2010).

A focus in pluvial flood risk management is on early warning and response. Van Ootegem et al. (2015) found that being aware of the pluvial flood risk before the water enters the building reduces content damage on average by 90% in the case of basement floods and by 77% in the case of ground floor floods. However, early warnings for pluvial floods are challenging, as they require the combination of heavy rainfall forecasts or at least nowcasts with a high spatial and temporal resolution as well as local information about the urban drainage system, topographic data, land use and soil moisture preconditions. Although pluvial flood early warning systems are often limited to rainfall forecasts with warning levels based on historical events or previous flood experience, more advanced systems have been implemented on different spatial scales in recent years (Henonin et al., 2013; Leitão et al., 2010). The city of Marseilles, France for example runs a warning system that links rainfall intensities with local flooding thresholds (Parker et al., 2011; Deshons, 2002). In the UK, a new system for extreme rainfall alerts and a surface water flooding forecast was introduced after the severe pluvial floods in 2007, which is currently further improved by implementing the Grid-to-Grid (G2G) model (Ochoa-Rodríguez et al., 2018). For the case study areas in Germany, pluvial flood warning is restricted to severe weather warnings on district level issued by the Deutscher Wetterdienst (DWD). These severe weather warnings have a maximum lead time of 12 h and mostly contain the expected maximum rainfall intensities for the respective district in case of a forecasted heavy rainfall event (DWD, 2016*a*,*b*). The effectiveness of flood early warning systems in reducing damage is mainly determined by lead times, water depths, and the availability and ability of people to undertake emergency measures effectively (Penning-Rowsell and Green, 2000; Kreibich and Merz, 2006). The commonly short lead times for pluvial floods are a challenge, in contrast to the generally shallow water levels, which allow a damage reduction by sealing the building or by moving contents higher, e.g., onto shelves or in higher stories. The ability to undertake effective measures is, for instance, supported by recent flood experience, good preparation and the availability of emergency plans (Thieken et al., 2007; Kreibich et al., 2007). Since flood experience may be commonly lacking due to the rare and local occurrence of pluvial flood events, specific risk communication seems to be decisive for increasing preparation and an effective implementation of emergency measures.

Damaging processes during pluvial flooding are distinguished from fluvial flooding as the sources of the excess water and flow processes are very different. Due to a lack of detailed damage data, there is not much information about damaging processes available. Results of decision-tree analysis show that insurance claim frequency related to torrential rain and pluvial flood damage to property is most strongly associated with maximum hourly rainfall intensity, followed by real estate value, ground floor area, household income, season and the age of the building (Spekkers et al., 2014). A study on pluvial flood damage in Belgium found that, although flood depth is an important predictor of pluvial flood damage, indicators that are not related to flood characteristics, including building properties, behavioral predictors and income, are also important (Van Ootegem et al., 2015).

The objective of this paper is to gain better knowledge about the consequences of pluvial floods and their management. How private households during three different pluvial flood events in Germany were able to cope with the flooding is investigated. Following the phases of the risk management cycle, how private households contributed to damage mitigation and how preparedness, response and recovery are correlated to socio-economic variables, flood experience and flood impact is analyzed.

2.2 Pluvial flood events

2.2.1 Pluvial flood event in the town of Hersbruck on 29 June 2005

At the end of June 2005, the weather in Western Europe was influenced by a surface low (named Yassin by Institute for Meteorology, FU Berlin, Germany) that emerged over Spain on 28 June, moved northeast, crossed France and reached Germany on 29 June. It brought warm humid subtropical air from the southwest of Europe. Along the boundary zone, due to cold and dry air masses from the north, the atmosphere became more and more unstable and thunderstorms with heavy rainfall, storm gusts, lightning strokes and hail developed mainly in the western (North Rhine-Westphalia, Hesse, Rhineland-Palatinate, and Saarland) and southern (Baden-Wuerttemberg and Bavaria) parts of Germany. Hersbruck, a town in Bavaria, 27 km northeast of Nuremberg, was also highly affected by torrential rain. The first moderate rainfall occurred from 8:00 A.M. to 11:00 A.M. (Central European Time) on 29 June. At about 10:00 P.M., rainfall started again with the highest intensity from 10:00 P.M. to 11:30 P.M. Until 7:30 A.M. on 30 June the meteorological station Hersbruck recorded 115.8 mm in 24 h, and until 7:30 A.M. on 1 July 117.3 mm within 48 h. Approximately 110 mm fell within only 1.5 h in the late evening on 29 June. The 1 h, 24 h and 48 h rainfall return periods exceeded 100 years (URBAS, 2008).

The heavy rain caused widespread flooding and damages in the city of Hersbruck for various reasons. Flash floods with sludge and debris from unsealed areas outside the town damaged houses. Several small creeks overtopped the banks, whereas the rise of the water level of the River Pegnitz in Hersbruck did not cause any damages. At least two landslides occurred, one of them buried a street over a distance of about 50 m. The sewer system was hydraulically overloaded, and streets and underpasses were flooded. Some stormwater overflow structures were also overloaded and newly built reservoirs in Hersbruck-Weiher were heavily damaged. Approximately 300 houses (mainly the basements) were affected, and, in two cases, leaking heating oil contaminated the water. Several underground car parks were flooded and a number of cars were damaged. The total damage was estimated at approximately EUR 2.8 million. Besides the described event, several smaller pluvial floods in different parts of Hersbruck were reported for the years 1995–1997 and 1999 (URBAS, 2008).

2.2.2 Pluvial flood event in the town of Lohmar 29 June 2005

The weather situation that triggered the pluvial flood event in Hersbruck (see Section 2.2.1) was also responsible for the development of thunderstorms in the western part of Germany. Lohmar, a town in North Rhine Westphalia, 20 km southeast of Cologne, was also affected. Here, the first moderate rainfall occurred in the early morning hours (1:00 A.M. to 7:00 A.M. Central European Time) on 29 June. At about 6:00 P.M., rainfall started again until 4:00 A.M. on the next day, with the highest rainfall intensity between 9:00 P.M. (29 June) and 1:00 A.M. (30 June). Until 7:30 A.M. on 30 June, several meteorological stations in Lohmar and surroundings recorded 54 to 68 mm in 24 h. In the evening hours of 30 June until the morning of 1 July, thunderstorms once again brought heavy but less intense rainfall. Until 1 July (7:30 A.M.), rainfall accumulated to 86 to 112 mm within 48 h. Locally, the 48 h rainfall return period exceeded 100 years (URBAS, 2008).

The heavy rain led to flooding in the city area of Lohmar and surrounding city districts, mainly from overflowing small creeks such as the Jabach, the Auelsbach and other very small unnamed creeks (tributaries to the River Agger) because of hydraulic surcharge, especially at throats like bridges or at culverts that were partly blocked with sludge and driftwood. The water level of the River Agger in Lohmar also rose but did not exceed the warning stages. Locally, the sewer system was overloaded and at some places water from the surrounding agricultural land flooded built-up areas. Some areas were flooded twice, initially in the night 29/30 June, and again approximately 24 h later (30 June/1 July).

Besides the school center, the control center of the fire brigade of Lohmar was affected, and a temporary office had to be established. Generally, mainly basements, altogether 250 according to newspaper articles, were flooded. One affected company lost its whole archive. Most operations by the fire brigade and the Federal Agency for Technical Relief (THW) took place in the city area of Lohmar and in the surrounding districts Donrath and Wahlscheid. The total damage was estimated at approximately EUR 2.4 million. While there is no history of pluvial floods reported for Lohmar, the town has suffered from one reported fluvial flood before 2005, caused by the Auelsbach, a tributary of the River Agger in the year 2000 (Lohmar, 2005).

2.2.3 Pluvial flood event in the city of Osnabrück 27 August 2010

In all of Germany, August 2010 was the wettest August since 1881, when regular precipitation measurements started (Booß et al., 2010). Locally, the monthly rainfall total exceeded the average amount by almost four times, e.g., in the city of Osnabrück, which is, with 156,000 inhabitants, the fourth biggest city in Lower-Saxony in the northwest of Germany (see Figure

2.1). In August 2010, it received rainfall totals of 273 mm, which is 385% of the reference value (NLWKN, 2010).

During the summer of 2010, the Northern Hemisphere jet stream was characterized by a strongly meandering pattern that remained locked in place for several weeks and brought extreme weather conditions to different regions in the Northern Hemisphere (Schubert et al., 2011; Coumou and Rahmstorf, 2012). Low pressure systems repeatedly brought moist air with thunderstorms and heavy rain to Central Europe. While in the first half of the month (6 to 10 August), the most damaging flood event occurred at the River Neiße at the German–Polish–Czech border, heavy rainfall events between 26 August and 2 September led to major urban flooding in several places damaging a total of 8000 buildings claiming insured losses of EUR 35 million (GDV, 2012). During this episode, the city of Osnabrück was the most severely hit district: while the average damage per affected building in late August 2010 was EUR 4840 in all of Germany, it was to EUR 6249 in Osnabrück (GDV, 2012). The damage was caused by a severe weather system that dumped 128 mm of rain across the city on 26 August, which equals 47% of the mean monthly precipitation in August. As a result, the creeks Hase, Düte and Belmer Bach could not drain the water and inundated parts of the city, particularly the neighborhoods of Lüstringen, Hellern, Fledder, Atter and Atterfeld. For the first time since the Second World War, Osnabrück's mayor declared a state of emergency. Although this event was the most severe flood recorded in the history of Osnabrück, there have been two smaller fluvial flood events caused by the River Nette in 1998 and by the River Hase in 2008 (Osnabrück, 2016*a*).

2.3 Data and methods

2.3.1 Surveying private households affected by pluvial flooding

The data for all three case studies were collected by computer-aided telephone interviews (CATI). Interviews were conducted among households in the flood affected areas of Lohmar and Hersbruck 17 months after the event. On the basis of information from fire brigades, street lists were compiled and the telephone numbers of residents, potentially affected by the pluvial flood, were searched from public telephone directories. In Lohmar, 742 telephone numbers could be identified, while, in Hersbruck, 534 were identified. During the survey period from 21 November to 19 December 2006, all telephone numbers were contacted. In total, 62 interviews in Lohmar and 111 in Hersbruck with affected residents were completed, which corresponds to 14% of the collected telephone numbers (1,276). Fifty percent of the households called had not been affected by flooding at all, or the building was mainly used for commercial purposes; 25% did not want to participate in the survey; 10% were not reachable during the survey period; and 1% did not complete the interview. In the survey, the term "affected" was defined as a household that had suffered (financial) flood damage at the end of June 2005. Before the start of the telephone interviews, the public was informed about the campaign. Flyers with information on pluvial flooding in general and the campaign were distributed to all households in the affected areas in Lohmar and Hersbruck, and press releases were issued in the local media. In Lohmar, information was also available on the municipal website.

While the data from Lohmar and Hersbruck were gathered by a dedicated campaign within the project Urban Flash Floods (URBAS), the data from Osnabrück were part of a larger data collection campaign among private households, which suffered from property damage caused by flooding in August 2010 or January 2011 in Germany. The survey was conducted in February/March 2012, about nineteen months after the respective pluvial flood event. Lists of inundated streets were compiled on the basis of official flood and media reports as well as flood masks derived from satellite data (ZKI, Centre for Satellite-Based Crisis Information).

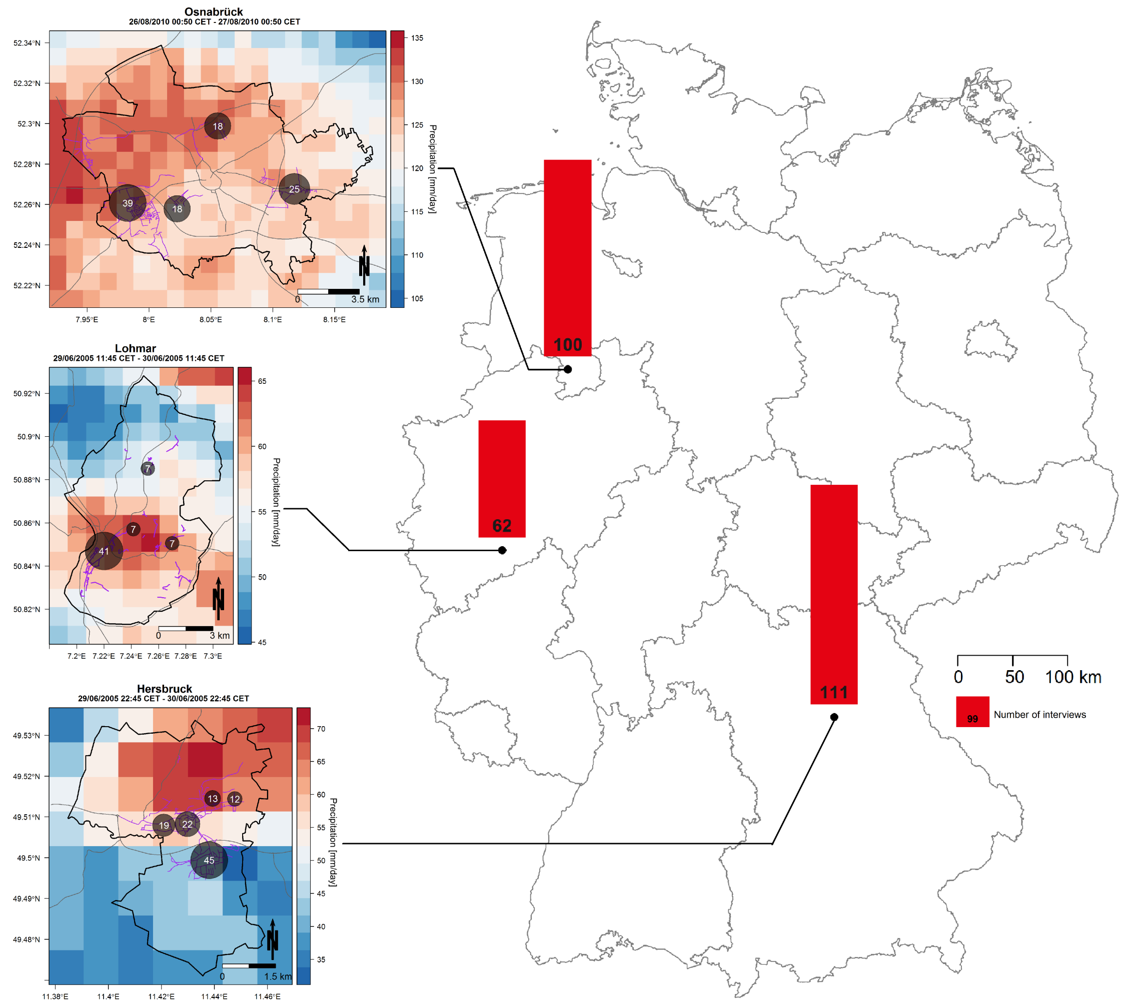

Figure 2.1: Spatial distribution of rainfall amount (24 h precipitation radar data), affected streets (**purple**) and number per interviews per neighborhood (**grey bubbles**) for the study areas **(a)** Osnabrück; **(b)** Lohmar; **(c)** Hersbruck; **(d)** location of the study areas and number of completed interviews per study area.

With the help of these lists, which contained 143 street names from Osnabrück phone numbers of all potentially affected residents were searched from the public telephone directory. In total 20,332 phone numbers were contacted. However, the percentage of successfully completed interviews was rather small in the end (3%). One reason for this was imprecise information on the (maximum) flood area and affected streets derived from this data, with the result that about 40% of households called had not been affected by flooding at all. Therefore, a more detailed documentation of the flood extent would be of great benefit for the overall sampling efficiency.

The survey campaign resulted in 658 completed interviews, of which 100 interviews were carried out with residents affected by torrential rainfall in the city of Osnabrück in August 2010. Their spatial distribution is displayed in Figure 2.1. A comprehensive analysis of the interviews in respect to the fluvial floods, that were excluded from this paper, can be found in Kienzler et al. (2015).

The questionnaires used in both campaigns (2006 and 2012) were slightly modified versions of a questionnaire originally developed by Kreibich et al. (2005) and Thieken et al. (2007) for the 2002 flood in the Elbe and Danube catchments. The interviews lasted 25 to 30 min on average and the questionnaire consists of approximately 110 questions on the following topics (in the order of appearance):

- Characteristics of the flood event;
- Early warning and emergency measures;
- Contamination of the floodwater;
- Evacuation;
- Clean-up work and recovery;
- Physical and financial flood damage to the building and the household contents;
- Building ownership and further information on the residential building (or the rented apartment);
- Aid and financial compensation;
- Long-term preventive and protective measures undertaken by the affected household and motivation (not) to do so;
- Previously experienced flood and flood awareness; and
- Socio-demographic information.

In a number of questions, people were asked to rank qualitative or descriptive variables on a scale from 1 to 6, where “1” described the best case and “6” the worst case. The meaning of the end points of the scales was given to the interviewee. The intermediate rankings could be used to graduate the evaluation. The surveys were conducted with the VOXCO software package by the Explorare market research institute. In all interviews, the person in the household that had the best knowledge about the flood damage was interviewed.

2.3.2 Pluvial flooding dataset

The total amount of 273 interviews in the dataset consists of 111 households for the town of Hersbruck, 100 households for the town of Osnabrück and 62 households for the town of Lohmar. With approximately 300 affected households in Hersbruck, 250 in Lohmar and 1100 in Osnabrück, sample fractions of 37%, 25% and 9%, respectively, were reached for the three subsets (URBAS, 2008; NOZ, 2016). An overview of the characteristics for the three subsets regarding socio-economic and flood impact variables is shown in Table 2.1. Compared to recent census data, the mean age, household size, and mean living area is higher in the sample for all three subsets. This is also true for the homeowner rate, which is considerably higher compared to the census reference (see Table 2.1). As mentioned in a previous study by Kienzler et al. (2015), this points towards a methodological bias of telephone interviews, where only phone numbers listed in the central telephone register are considered in the sample. An increasing use of cell phones and the fact that new landline numbers are not automatically added to the central telephone register, might lead to an overrepresentation of homeowners and long-established households.

Looking at education and income of the respondents, there is a considerable heterogeneity between the three study areas. While in Osnabrück 52% of the respondents stated to have a higher education, in Hersbruck this number is with 23% considerably lower. This is also reflected in the monthly net household income, where Osnabrück has the lowest fraction of low income households with less than EUR 1500 at 14% and Hersbruck the highest fraction with 25%.

Table 2.1: Socio-economic variables and flood characteristics for the three study areas. The values in brackets show the reference values based on data from the census in 2011.

Pluvial Flood Event		**29 Jun 2005**		**27 Aug 2010**
Area		**Hersbruck**	**Lohmar**	**Osnabrück**
Interviews	n	111	62	100
Affected households (est.)	n	300[1]	250[1]	1,100[2]
Sample Size	%	37	25	9
Total population	n	12,000[3]	31,000[4]	156,000[5]
Socio-Economic Variables				
Mean age of respondents	yr	52 (44[6])	50 (43[6])	55 (42[6])
Respondents with higher education	%	23 (25[6])	39 (34[6])	55 (41[6])
Mean household size	n	2.6 (2.2[6])	3.0 (2.4[6])	2.6 (2.0[6])
Households w. net income (pm) <1500€	%	25	19	14
Mean living area	m^2	106 (99[6])	126 (112[6])	112 (86[6])
Home owner rate	%	61 (54[6])	82 (66[6])	85 (35[6])
Flood Impact Characteristics				
Mean flood duration	h	10	11	23
Mean water level (rel. to surface)	cm	-108	-138	-108
Median water level (rel. to surface)	cm	-136	-181	-30
Reported high/very high flow velocities	%	18	33	12
Reported only basement affected	%	80	89	90
Reported contamination (sewage, oil, gas)	%	25	24	34

[1] Report URBAS Project(URBAS, 2008)
[2] Neue Osnabrücker Zeitung (local newspaper) (NOZ, 2016)
[3] Bavarian State Office for Statistics (LfStat, 2014)
[4] Archive of the city of Lohmar, (Lohmar, 2005)
[5] The city of Osnabrück, Department for Urban Development (Osnabrück, 2016*b*)
[6] German Federal Office of Statistics (DESTATIS, 2016)

Regarding education and income the Lohmar sample lies just between the two other subsets. Comparing the three subsets in respect to their flood impact characteristics, small differences can be seen for the median water level, mean flood duration, the flow velocity distribution and the fraction of contaminated households (see Table 2.1). Given the flood characteristics as well as the number of affected households, Osnabrück can be characterized as the most severe flood event among the three subsets.

The differences in the rainfall intensity and amount outlined in Section 2.2 between the events is also reflected in the water levels, where the median water level relative to the surface for Lohmar is 45 cm and 51 cm lower than in Hersbruck and Osnabrück, respectively (see Table 2.1). The negative mean and median water levels indicate the high fractions of households where only the basement was affected.

In contrast, the mean flood duration in Osnabrück was considerably longer than it was in Hersbruck and Lohmar. This is caused by the high number of affected households in Osnabrück compared to the smaller events in Hersbruck and Lohmar, which exceeded the coping capacities of the local emergency services. According to local newspaper reports, this led for some households to a delay of several hours, before their flooded basements could be pumped out by the emergency services (NOZ, 2016).

In Lohmar, the fraction of respondents reporting high or very high flow velocities near their house is considerably higher than in Hersbruck and Osnabrück. Differences can also be observed for respondents, who reported contamination of their property during the flood. Osnabrück sticks out with 34% of the interviewed households reported a contamination of their property with either oil, sewage, gas or other chemicals.

2.4 Results and discussion

The results presented in this section follow the widely used risk management cycle (see (Thieken et al., 2007; DKKV, 2003; Silver, 2001)), which addresses the following phases before, during and after a pluvial flood event:

- Preparedness: This section discusses the previous flood experience of the respondents in all three subsets, the private precautionary measures they had taken to mitigate the flood risk and their motivation to undertake these measures.

- Warning and response: This section discusses whether the respondents received a warning prior to the event and if they undertook any measures shortly before or during the event to reduce damage.

- Flood damage: This section discusses the damage to buildings and contents caused by pluvial floods in the three study areas and possible factors that influence the amount of damage.

- Recovery: This section discusses the process that lead to regaining the standard of living after the pluvial flood events compared to the pre-event conditions and the factors that influence the recovery after such an event.

2.4.1 Preparedness

Several studies have shown that flood experience and knowledge about the flood hazard (among other factors) are closely connected to the implementation of precautionary measures (e.g. Thieken et al., 2007; Kreibich et al., 2005; Bubeck, Botzen and Aerts, 2012; Kreibich, Seifert, Thieken, Lindquist, Wagner and Merz, 2011; Siegrist and Gutscher, 2006). Therefore, flood experience and preparedness, in the form of private precautionary measures, are considered together in this section.

Flood experience and knowledge about the flood hazard

Looking at the overall flood experience, the fraction of respondents, who have experienced a flood before the respective events in 2005 and 2010, is rather low in all three case studies. The same is true for the knowledge about the flood hazard among the respondents, who had not experienced a flood before (see Table 2.2).

Table 2.2: Flood experience and knowledge about the flood hazard among private households in each study area.

Pluvial flood event	**29 Jun 2005**		**27 Aug 2010**
	Hersbruck	**Lohmar**	**Osnabrück**
Flood experience prior to the respective event (%)			
Respondents who experienced at least one previous flood	26	16	22
Respondents who experienced at least one previous flood less than 10 years ago	17	3	11
Respondents who have not experienced a flood prior to the respective event	73	84	78
Respondents who have not experienced a previous flood, but have knowledge about the fl. hazard of their property	16	10	8

With only 16% of respondents having previous flood experience, the Lohmar subset has the lowest number of flood experienced respondents among the three case studies. When only taking floods into account that happened less than 10 years ago from the respective event, flood experience in Lohmar was almost non-existent with only 3%. Comparing the two simultaneous events in Lohmar and Hersbruck, a considerably higher amount of respondents in the latter area had experienced a flood before the 2005 event. There is also a higher amount of respondents in Hersbruck, which had knowledge about the flood hazard, although they had no previous flood experience.

Overall, the Hersbruck subset has the highest fraction of flood experienced respondents, as well as respondents with knowledge about the flood hazard among the three subsets. For the other two subsets, the flood experience differs considerably, while the knowledge about the flood hazard is equally low for Lohmar (10%) and Osnabrück (8%). Since pluvial floods also occur in areas not obviously prone to flooding and where flood maps are non-existent, these results seem to correspond with the flood history of the three study areas before the respective events (see Section 2.2).

Therefore adding information on pluvial flood risks to existing flood maps could help to increase the awareness of pluvial flood risk in the general public.

Precautionary measures

Private precautionary measures are an important part of flood loss mitigation. The study comprises three different levels of precautionary behavior: (1) low-cost measures, such as acquiring information about flood protection; (2) medium-cost measures, such as an inferior use of exposed floors; and (3) high-cost measures, which involve structural changes to the building. In total, eleven precautionary measures, covering all three levels, were considered in the questionnaire (see Figure 2.2).

The Osnabrück study contained three additional measures, which are, for the sake of comparability between the three subsets, not considered in this study. Although taking out flood insurance does not have a direct effect on flood loss mitigation, it helps to recover faster from a flood event and is therefore treated as a medium-cost measure in this study. For all measures, the respondents were asked to state whether the measure had been implemented before the flood, after the flood, is planned or will not be implemented. Measures that involve changes to the building structure were only answered by homeowners, as tenants are usually not able to implement these measures. In this section, the changes in preparedness before and after the respective event as well as the motivation to undertake precautionary measures will be discussed.

Preparedness before the flood

Although the flood experience and knowledge about the flood hazard was low (see Section 2.4.1 - *Flood experience and knowledge about the flood hazard*), the overall preparedness for pluvial floods in terms of respondents who did undertake at least one precautionary measure before the flood events in 2005 and 2010 was with 60% surprisingly high. Compared to similar analysis by Kienzler et al. (2015) for fluvial floods where 90% of all respondents did undertake at least one precautionary measure before the flood, the value can still be seen as high against the backdrop of the lower flood awareness of the general public for pluvial floods (Houston et al., 2011). However, differences in preparedness between the three subsets can be observed. In Osnabrück, 67% of the respondents undertook at least one measure before the flood, while the values for Hersbruck (59%) and Lohmar (48%) are lower. Interestingly, the flood experience and knowledge in Osnabrück was lower, than in Hersbruck, but still resulted in a higher fraction of households who undertook precautionary measures.

Regarding the different precautionary measures implemented by the interviewed households, an overview is given in Figure 2.2. Mostly low-cost and medium-cost measures were undertaken before the event. Among the households of all three subsets, collecting information about flood protection (22%), collecting information about the flood hazard (21%) and effecting flood insurance (21%) were the most common precautionary measures undertaken before the respective flood event. Although collecting information about the flood hazard and how to protect against floods, as well as contracting a flood insurance have no direct effect on the reduction of flood damage, the high fraction of low-cost measures must be seen in context of cost-effectiveness in regard to flood probability and expected damage (Kreibich, Christenberger and Schwarze, 2011). While high-cost measures are often economically “reasonable” in relation to the expected damage for fluvial floods with short return periods, small pluvial floods with typically lower amounts of loss call for a shift from expensive precautionary measures to less costly solutions (Poussin et al., 2015). This is also true for measures that are able to directly reduce damage, where medium-cost measures, such as adapted building use were more common than expensive changes to the building structure. Among the medium cost-measures, installation of a backflow preventer (20%) and avoiding expensive permanent interior on floors at risk (19%) were the most popular measures to mitigate flood damage. With 3% to 7% of all respondents, high-cost measures were only considered by a minority.

When looking at the three subsets separately, only smaller differences in precautionary behavior can be identified. Overall, the level of precaution for Osnabrück was slightly higher than for the events in Lohmar and Hersbruck. For seven out of eleven measures, the fraction of respondents who did implement this measure before the flood was higher in Osnabrück than in Lohmar and Hersbruck (see Figure 2.2). This includes all high-cost measures, except for the installation of permanent or mobile water barriers. When looking only at the Lohmar and Hersbruck subsets, it is interesting to see, that although Lohmar had a higher number of

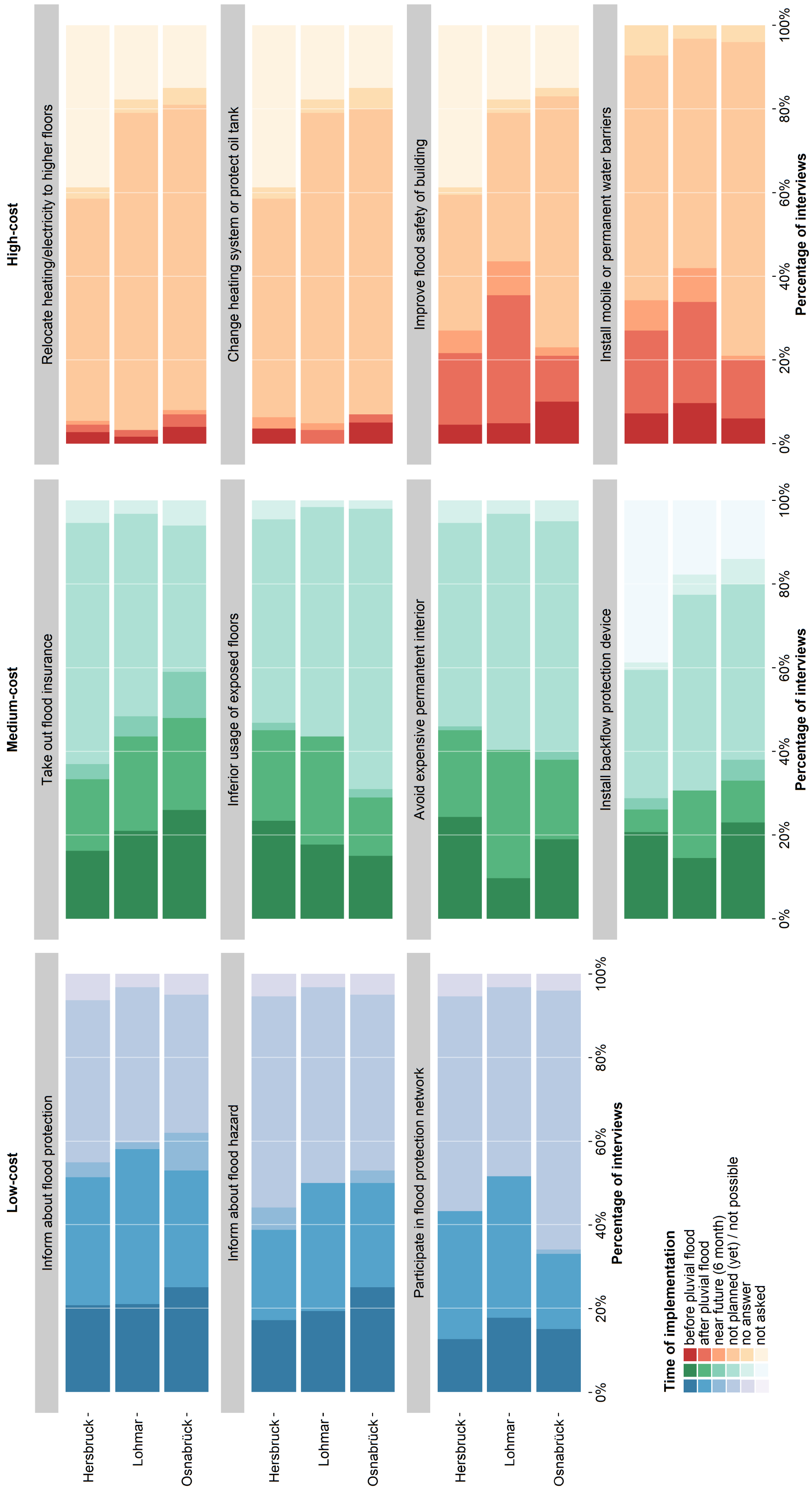

Figure 2.2: Private precautionary measures undertaken by event, time of implementation and costs.

respondents who informed themselves about the flood hazard, how to protect against floods and who joined a flood network, these measures did not translate to the same extent into actual damage mitigation measures. Hersbruck, on the other hand, shows lower or equal numbers for measures that involve acquiring information about pluvial floods, but has higher values than Lohmar for almost all measures involving adapted building use and changing the building structure. For the two adapted building use measures "inferior use of exposed floors" and "avoidance of expensive permanent interior on floors at risk", the values of 23% and 24%, respectively, are even higher than in Osnabrück. In comparison with a similar study on fluvial floods by Kienzler et al. (2015), the values for all three study areas are in the range of the 2002 flood along the River Elbe, where the preparedness level was considered low. Interestingly the recent history of pluvial flood events in Hersbruck (see Section 2.2.1) did not seem to have an effect on the implementation of precautionary measures, as the values for almost all of the measures are equally low as for the other two study areas, where no recent pluvial flood events prior to the events of 2005 and 2010 were reported. However, the low flood experience (see Table 2.2) indicates that during past events other areas of Hersbruck were affected, remaining the households that were hit in 2005 unaware of the risk. This highlights the local extent of pluvial floods, which make an adequate preparedness challenging for private households as well as for local authorities.

Changes in preparedness after the flooding

For all three subsets, the respondents were not only asked about what precautionary measures they have undertaken before they were flooded, but also whether they changed their precautionary behavior in the aftermath of the flooding. Implementing precautionary measures in the aftermath of a flood is not only a comprehensible behavior, but can also be understood from an economic perspective, as implementing these measures alongside the restoration of a damaged building is seen as very cost-effective (Kreibich et al., 2005). Grothmann and Reusswig (2006) reported that homeowners often implement mitigation measures when they renovate or repair the building - for any other reason. Therefore, it is not surprising that a significant rise in precautionary behavior after all three events can be observed. The strongest absolute increases subsequent to the flooding can again be mainly seen for low- and medium-cost measures. With 31% in total for all three subsets, informing about flood protection was the most popular measure undertaken after the flood. However, the strongest relative increases can be observed for improving the flood safety of the building (this includes structural changes to the buildings as well as installing flood proof basement doors and windows) and installing mobile or permanent water barriers. While the latter two were implemented by only 7% of all respondents before the flood, this value rose by 19% for installing mobile water barriers and 18% for improving the flood safety of the building subsequent to the flooding. Very expensive measures such as relocating the heating system and fuse box to higher floors or completely changing the heating system, was only considered by very few respondents (<5%) before the flood and did not change much after the flood.

When looking at the three subsets individually, Lohmar showed for most of the measures a considerably higher increase after the flood, than Hersbruck and Osnabrück. Being the least prepared subset before the flood, Lohmar shows the highest absolute values of respondents who informed themselves about flood protection (57%), participated in flood protection networks (52%), improved flood safety of their building (31%) and installed permanent or mobile water barriers (34%) after the pluvial flood. Nevertheless, for all three subsets, the number of respondents who reported the implementation of a measure doubled for most of measures after the flood event.

Motivation to undertake precautionary measures

In order to analyze whether flood experience or knowledge about the flood hazard has a significant influence on implementing precautionary measures as stated by several studies on fluvial floods (Bubeck, Botzen and Aerts, 2012), Chi-squared tests with a 0.005 significance level were performed. Therefore the interviewed households were separated into groups depending on whether they have implemented no or at least one precautionary measure for each cost-level (low-, medium-, high-cost measures) (Figure 2.3). Looking at the flood experience, only low cost measures were significantly more often implemented by households who have knowledge about the flood hazard but no previous flood experience. A possible explanation could be that households who had been flooded before considered inexpensive measures as sufficient given the flood probability and expected future damage. Households with only knowledge about the flood hazard might assess the risk as well as the expected damage higher and therefore considers larger investments in private flood precaution as feasible.

When asked about the general effectiveness of precautionary measures on a scale from (1), meaning "very effective" to (6), meaning "very ineffective", a majority of 69% in all three subsets evaluates precautionary measures as rather effective, giving numbers from (1) to (3). Among these, 24% consider private precautionary measures as "very effective". The differences between the three subsets are in accordance with the fraction of precautionary behavior shown in Figure 2.2: with 32% of respondents rating precautionary measures as "very effective" and 81% giving grades from 1 to 3, Osnabrück showed the highest fraction of respondents with positive attitude toward precautionary behavior (Figure 2.4). This is followed by Lohmar (rating (1): 24%; rating (1) to (3): 66%) and Hersbruck (rating (1): 17%; rating (1) to (3): 61%). Only a minority of 3% in Osnabrück, 5% in Lohmar and 8% in Hersbruck evaluates precautionary measures as very ineffective.

The low motivation to implement high-cost measures, the lacking influence of flood experience and knowledge about the flood hazard, and the fact that precautionary measures were assessed as effective by most households suggest that cost and effort for a measure may influence the decision about precautionary measures. However, further research especially in the context of flood coping appraisal is needed to gain a deeper understanding on the influencing factors of private pluvial flood precaution (Bubeck et al., 2013).

Overall, the level of precautionary behavior before the flood was rather low in all three subsets. Possible reasons are lacking flood experience and knowledge about the flood hazard. Although precautionary measures were evaluated as a rather effective way to mitigate pluvial flood damage in general, mainly inexpensive and easy to implement measures were considered by households in all three study areas. These measures do not necessarily help to directly reduce damage, but must be seen against the backdrop of low risk awareness and the relation between costs of implementation and expected damage associated with pluvial floods. However, in consequence of the flooding, the fraction of respondents showing precautionary behavior more than doubled for many measures after the flood, and thus improving the preparedness of Lohmar, Hersbruck and Osnabrück for possible future floods.

2.4.2 Warning and response to pluvial flooding

Early warning

Receiving a warning prior to a pluvial flood increases the chances to adequately protect lives and assets at risk, by implementing emergency measures such as moving values to higher grounds, protect oil tanks or directly safeguard the building from inflowing water. In order to have enough time to implement these measures, the lead time as well as the content of the warning concerning affected areas and expected severity of the events, are critical. As

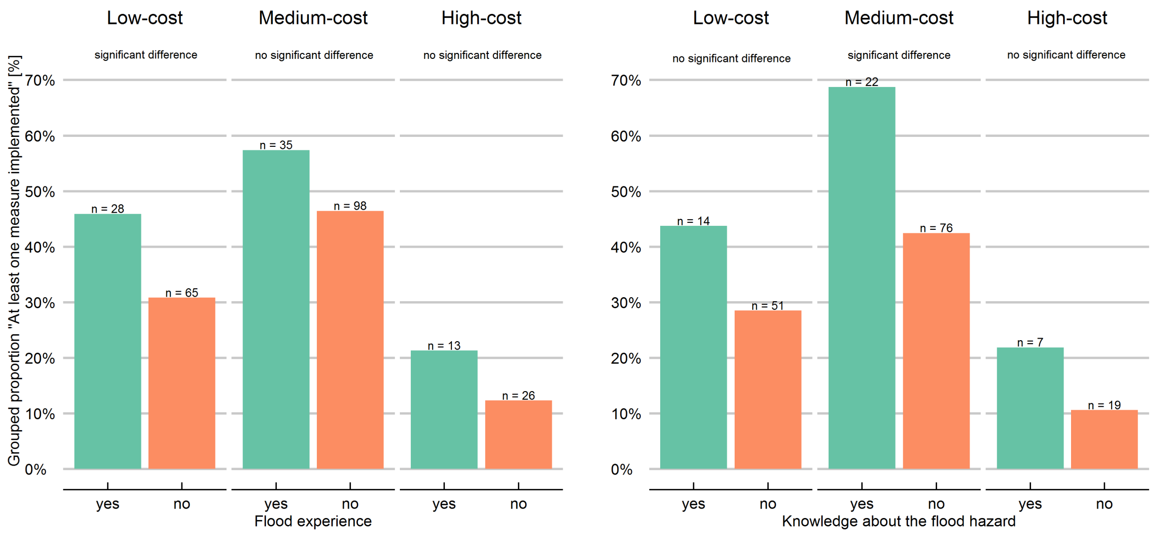

Figure 2.3: Percentage of households that implemented at least one precautionary measure split by flood experience and knowledge about the flood hazard for different cost levels.

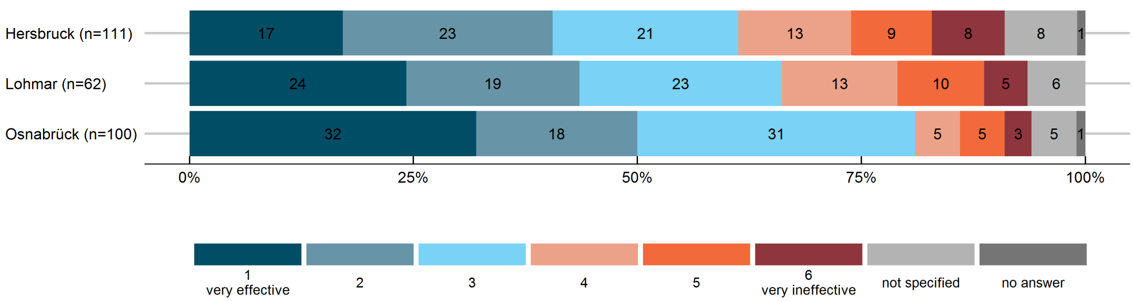

Figure 2.4: Perceived effectiveness of private precautionary measures for each of the three subsets on a scale from (1) very effective to (6) very ineffective.

outlined in Section 2.1, official early warnings for pluvial floods are challenging and limited to severe weather warnings released by the DWD (DWD, 2016*a*). Other warnings including warnings by friends or relatives, general news coverage or direct observation of the weather, are often uncertain and usually have considerably lower lead times compared to official warnings. For Hersbruck, Lohmar and Osnabrück, several severe weather warnings with maximum lead times of 17 h, 15 h and 16 h (meaning the time between the release of the warning and the flooding of the building), respectively, were released by the DWD. These warnings contained time, affected district and information about the expected amount of rainfall. Although for all three subsets official severe weather warnings were issued prior to the flooding, 68% of the interviewed households stated that they did not receive any warning (see Table 2.3). Among the respondents who reported that they have received a warning, with 19% most of them referred to own observations of the weather, the flooding of their direct surroundings or already smaller leakages inside their homes. This type of warning resulted in very short average lead times of less than two hours, which limits the emergency response to basic damage reducing

Table 2.3: Number and fraction of households who received or did not receive an early warning prior to the pluvial flooding event.

Sample area	**Hersbruck**		**Lohmar**		**Osnabrück**		**Total**	
	n	%	**n**	%	**n**	%	**n**	%
No warning received	86	77%	48	77%	53	53%	187	69%
Warning received	24	22%	13	21%	45	45%	82	30%
Severe weather warning	8	7%	3	5%	12	12%	23	8%
Own observation	12	11%	9	15%	31	31%	52	19%
Other warnings	4	4%	1	2%	2	2%	7	3%
No information	1	1%	1	2%	2	2%	4	1%
Total	111	100%	62	100%	100	100%	273	100%

measures, such as moving valuables to higher grounds or pumping out the water that already entered the building. Only 8% of all respondents received the official severe weather warning with an average lead time of nine hours prior to the event. The low number of recipients as well as the rather high delay of six to eight hours between the possible maximum lead time and the average lead time, indicates weaknesses in the dissemination of severe weather warnings. Meanwhile, the DWD has further improved the dissemination of warnings including various media channels such as Short Message Service (SMS), YouTube videos and an updated website design (DKKV, 2015).

The number of respondents who did not receive a warning was particularly high in Hersbruck and Lohmar, where in both cases 77% reported that the flood hit them without any warning. With 53% of respondents remaining unwarned, the value for Osnabrück was considerably lower.

Emergency measures undertaken

Emergency measures are actions that are taken shortly before or during a flood event to mitigate potential loss and damage (Maskrey, 1997). In the context of pluvial floods, emergency measures are expected to play an important role in damage reduction, as typically lower water levels compared to fluvial floods are assumed to make these measures particularly effective. However, the effectiveness of a particular measure in terms of damage reduction depends on a large number of factors, including the type of warning, lead time, the person implementing the measure, etc., and is still hardly understood (Molinari et al., 2013). For this study, the flood affected households in Lohmar, Hersbruck and Osnabrück were asked to report on the emergency measures they had undertaken and how they assess the effectiveness of these measures in order to reduce damage.

In total, 58% of all respondents reported to have implemented at least one emergency measure shortly before or during the pluvial flood. Among the eleven most common emergency measures asked, pumping the water out of the building (41%), putting movable contents upstairs (28%) and protecting the building from inflowing water (22%) were most often implemented by households in all three study areas. Although the relative popularity of each measure follows a very similar pattern in all study areas, considerable differences in the number of households implementing emergency measures in each study area were found. While in Osnabrück 68% of the households implemented at least one emergency measure, the numbers for Lohmar (58%) and Hersbruck (48%) are substantially lower. The most popular measures, such as pumping the water out of the building and putting movable content to higher floors, were particularly often implemented in Osnabrück. Besides switching off the gas and electricity supply in the building, Hersbruck falls behind the other two subsets for

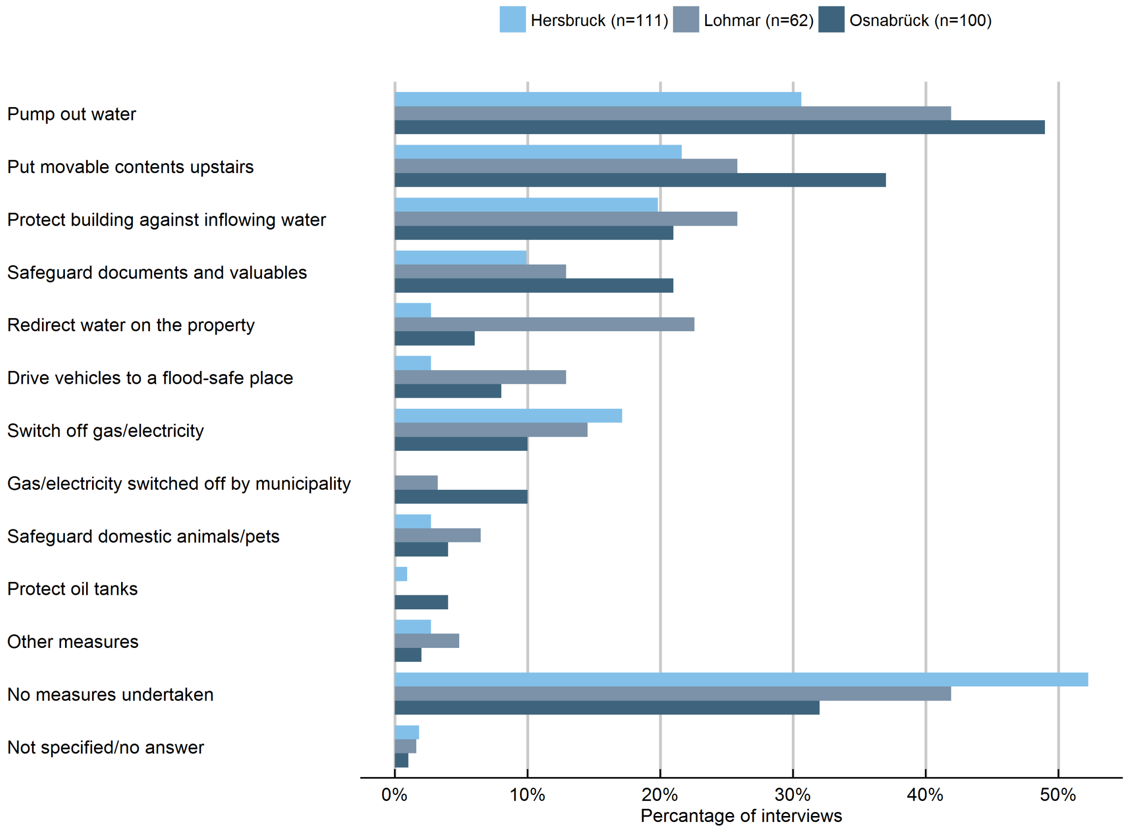

Figure 2.5: Fraction of interviewed households that performed emergency measures shortly before or during the pluvial flood event.

all other measures. However, the slightly higher number of households in Hersbruck who switched off their gas and electricity supply is probably due to the fact that apparently the municipality of Hersbruck did not switch it off centrally in the affected neighborhoods (see Figure 2.5). Compared to the other two subsets, a relative high percentage of households in Lohmar implemented measures such as protecting the building against inflowing water, driving vehicles to a flood-safe place and redirecting the water on the property. Unlike damage mitigation measures such as pumping out the water, the latter are often implemented with the goal to completely avoid losses by preventing water intrusion into the building or vehicle in the first place. A reason for this difference might be related to the hazard characteristics, as lower rainfall intensities (see Section 2.2) in Lohmar may have led to more households considering damage prevention as feasible.

The affected households in all three study areas were directly asked to assess the effectiveness of each emergency measure they have implemented on a scale from (1), meaning "very effective" to (6) meaning "very ineffective". For the three study areas, the average effectiveness of each measure is shown in Figure 2.6. Due to no or very few observations in the three study areas, "protecting oil tanks" was excluded as a measure from this analysis. With an overall average of (2) and averages ranging from (1) to (3.3) for each measure, the majority of the respondents assessed the implemented emergency measures as rather effective. Among the three study areas the measures implemented by households in Osnabrück were evaluated the most effective.

Table 2.4: Contingency table showing the number of respondents by implemented emergency measures and received warning (EM: emergency measure).

Emergency measure(s)		Warning received		Total
Total*		Yes	No	
	Yes	59	98	157
	No	27	89	116
Hersbruck*		Yes	No	
	Yes	17	37	54
	No	8	49	57
Lohmar		Yes	No	
	Yes	9	27	36
	No	5	21	26
Osnabrück		Yes	No	
	Yes	33	34	67
	No	14	19	33

* Proportions significantly different from each other based on a Chi-squared test with 0.05 confidence level.

When comparing the different measures, the ones that do not require special knowledge such as safeguarding documents and valuables or putting movable content upstairs are evaluated as more effectively compared to technical measures such as redirecting the water on the property or protecting the building from inflowing water. It is assumed that these differences are also related to the fact that the proper implementation of more elaborate emergency measures was constrained by short lead times in most cases.

Response to warning

In the case a household did not receive a warning at all, the lead time drops to zero making the proper implementation of emergency measures particularly difficult to almost impossible. In order to analyze if receiving an early warning (regardless of the lead time) influences the implementation of emergency measures, the fractions of respondents implementing at least one emergency measure were compared between groups who did or did not have received a warning prior to the respective flood event (see Table 2.4). A Chi-squared test between the proportions of all three study areas showed on a 0.05 significance level that significantly more households implemented at least one emergency measure when they had received an early warning. Looking at each event separately, one can see that for all three subsets the proportion of households who implemented at least one emergency measure is larger when a warning was received, compared to the group that did not receive a warning (Table 2.4). However, a significant influence on a 0.05 confidence level of receiving a warning on the implementation of emergency measures could only be confirmed for the Hersbruck subset. This indicates that not only the receipt of a warning is important for implementing emergency measures, but other factors such as the information provided in the warning, the flood experience and the capability of the respondent to implement measures are also important. Furthermore, the uncertainty that comes with severe weather warnings and forecasts in general, is often difficult to assess for private households and local authorities alike. Unlike fluvial floods, no clear thresholds are defined, when emergency services start implementing damage mitigation measures (Kox et al., 2015; Kox and Thieken, 2017).

In summary, the dissemination of the issued official early warnings was low in all three subsets, leading to short lead times for emergency response in most cases. Although in Osnabrück more people received a warning and implemented emergency measures than in the

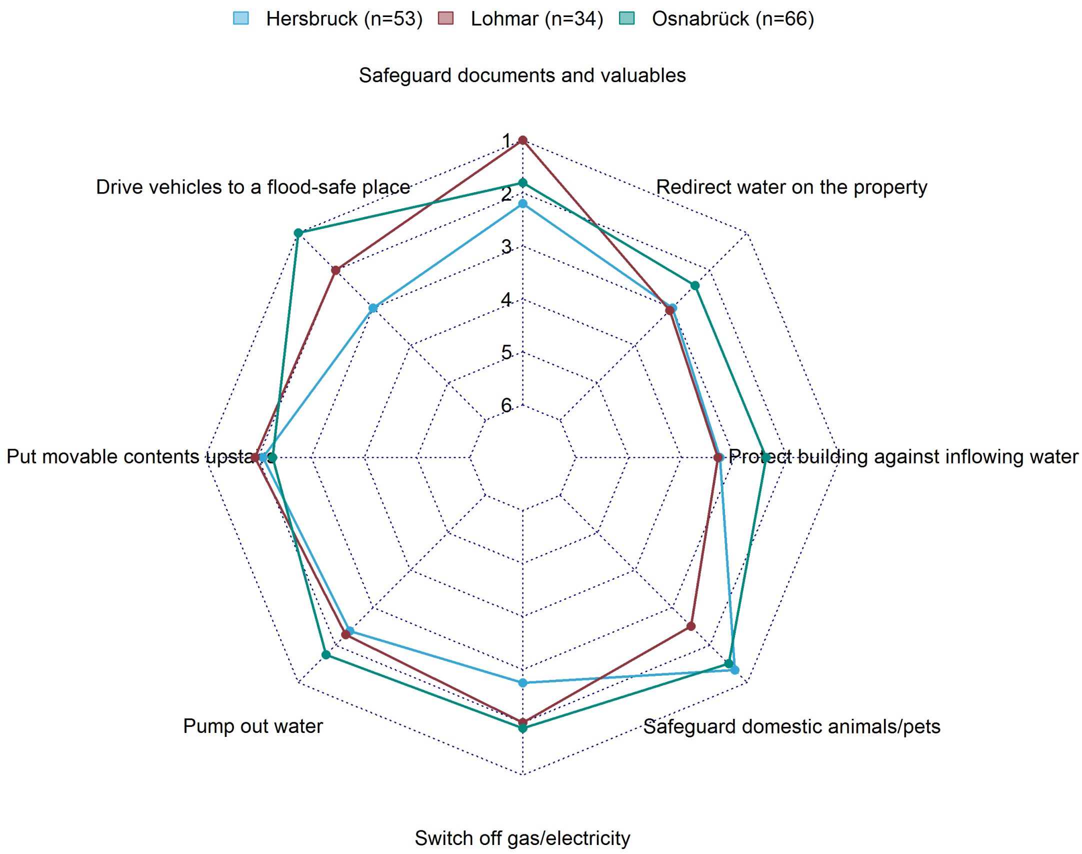

Figure 2.6: Average effectiveness on a scale from (1) "very effective" to (6) "not at all effective", evaluated by the respondents for each implemented measure. Data are shown for each study area.

other two subsets, a significant influence of early warning on the implementation of emergency measures was not found for this subset. This shows that receiving an early warning is only a first step in pluvial flood damage mitigation.

Therefore improving "(pluvial) flood intelligence" (Keys, 1993), meaning the ability to properly respond to a warning, is equally important to improving the dissemination of early warnings in order to reduce future pluvial flood losses.

2.4.3 Flood impact characteristics and resulting damage

Due to the high concentration of people and assets in urban areas, the potential damage caused by pluvial floods can be particularly high. Adverse effects caused by floods range from direct economic damage, when valuables get directly in contact with water to negative long-term health effects, such as trauma. Therefore flood damage is often categorized in direct and indirect damage as well tangible and intangible damage. First introduced by Parker et al. (1987) this scheme is frequently used in literature as a basis to classify different types of damage (e.g. Jonkman, 2007; Merz et al., 2010). This study focuses on the direct tangible damage to private households in terms of replacement values for building structure and contents. Respondents were only considered as "damage cases", when they reported monetary damage. For cases, were reported damage was only minor (e.g., "repainting the basement wall") and respondents were not able to quantify the damage, a flat-rate damage of EUR 250 was assumed.

Among the three subsets, 51% of the respondents reported damage to their residential building and 67% reported damage to contents. With 41% building damage and 71% content damage, the Hersbruck subset has the lowest fraction of respondents with building damage, but the highest fraction of respondents reporting content damage. The difference compared to the two other, for that matter, very similar datasets, is probably caused by the considerably lower homeowner rate in the Hersbruck subset (see Table 2.1). While homeowners are responsible for damage to their building as well as the contents, tenants can only be affected by content damage. However, in all three subsets the number of households reporting content damage is higher than the number of households reporting building damage. Compared to a similar study by Kienzler et al. (2015) on fluvial floods, a clear difference in damage characteristics between pluvial and fluvial floods can be observed. While more people suffered from building damage, than from content damage, in all five fluvial flood case studies analyzed by Kienzler et al. (2015), the numbers on pluvial floods just show the opposite. It can be assumed, that lower water levels during pluvial floods are not so harmful to building structures. Additionally, a lower preparedness in terms of adapted (basement) use in the case of pluvial floods, may lead to more damage to contents.

Table 2.5 shows the mean and median damage to building and contents for each event. To make the damage of the 2005 subsets comparable to the 2010 subset, the reported building and content damage for each household were corrected by the building price index and the consumer price index for consumer products excluding food for the year 2010, respectively (DESTATIS, 2015*b*,*a*). When comparing the mean and median damage for each event, as well as for contents and building damage, one can see that in all cases the mean values are higher than the median, indicating a positive skew of the damage distributions with higher damage frequencies on the lower range of the damage spectrum (Figures 2.7 and 2.8). The strongest difference between mean and median damage of EUR 12,322 can be found for building damage in Osnabrück (Table 2.5). This is partly caused by an overall shift of the damage distribution towards higher damage (see Figure 2.7), but mainly the effect of a few outliers with building damage over EUR 100,000. This can also be seen by comparing the corrected median building damage values for Lohmar and Osnabrück. Although the corrected mean building damage value for Osnabrück is almost twice as high as for Lohmar, the corrected median values are almost equal. Looking at the corrected average contents and building damage for each event separately, the results show, that average building damage in Osnabrück were high, while the average content damage is the lowest of the three subsets. Although Hersbruck and Osnabrück had similar hazard characteristics in terms of water levels and flow velocities (Table 2.1), the average building damage in Hersbruck was considerably lower, while the average content damage was slightly higher than in Osnabrück. Several factors, such as flood duration, contamination of the storm water, precaution, early warning and emergency response and flood experience have to be taken into account to explain these differences. However, content damage was lower in study areas where preparedness was higher, more households had flood experience, and received early warnings and/or implemented emergency measures. When comparing the three different subsets it can also be observed, that building damage seems to depend stronger on hazard characteristics such as flood duration, flow velocity or contamination of the flood water and is therefore more difficult to mitigate by non-structural precautionary measures and emergency measures.

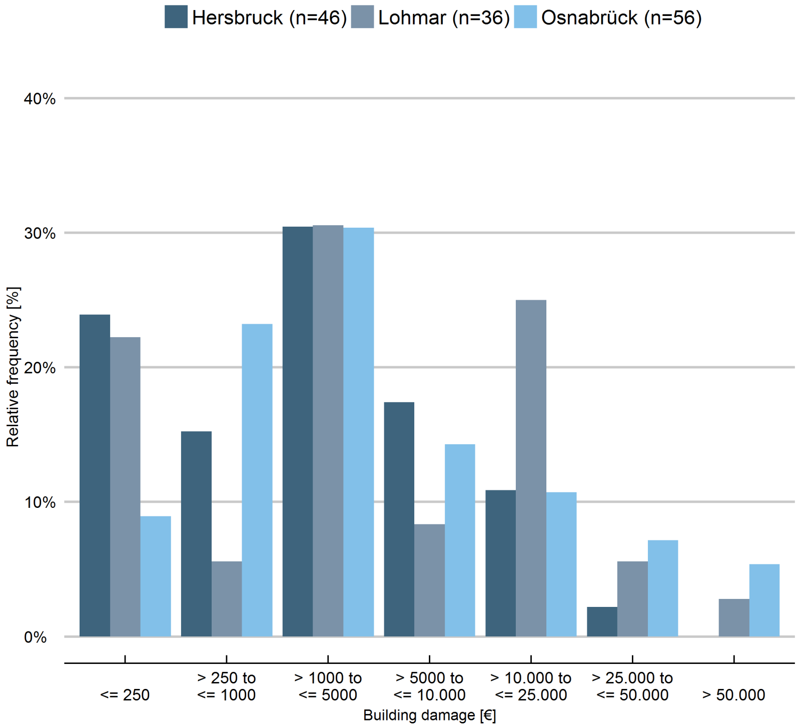

Figure 2.7: Distribution of classified building damage by study area based on inflation adjusted values.

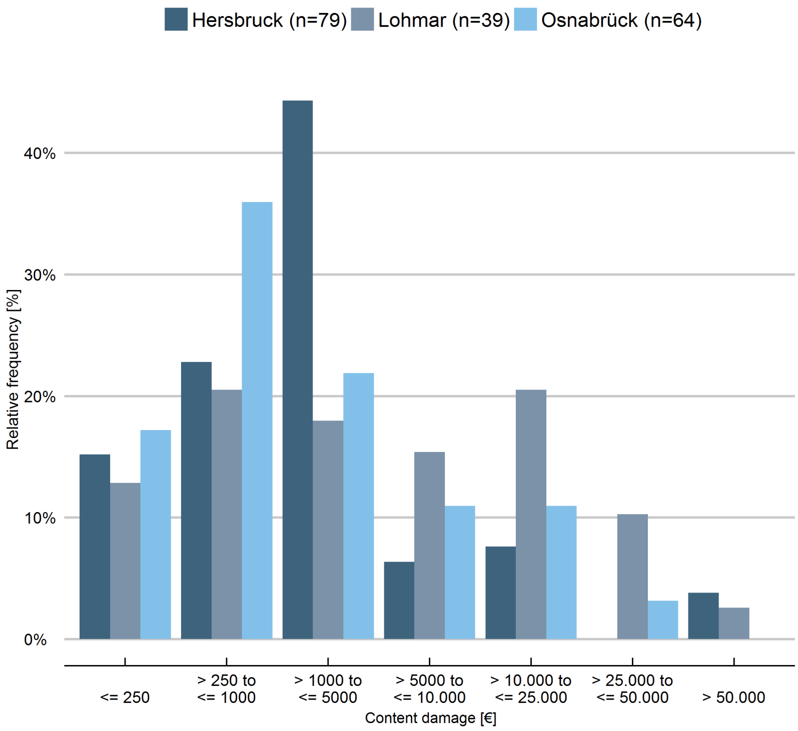

Figure 2.8: Distribution of classified content damage by study area based on inflation adjusted values.

Table 2.5: Damage to building and contents in the three study areas.

Flood event	**n**	**Reported** %	**Mean** Euro (€)	**Median** Euro (€)	**corr. Mean** Euro (€)	**corr. Median** Euro (€)
			Building damage			
Hersbruck	46	41	4,121	1,500	4,693[1]	1,708[1]
Lohmar	36	58	7,486	3,000	8,527[1]	3,417[1]
Osnabrück	56	56	15,322	3,000	15,322[1]	3,000[1]
			Contents damage			
Hersbruck	79	71	6,355	1,200	6,599[2]	1,246[2]
Lohmar	39	63	9,127	3,000	9,477[2]	3,115[2]
Osnabrück	64	64	4,685	1,000	4,685[2]	1,000[2]

[1] Damage values were corrected for the year 2010 based on the building price index ("Preisindizes für den Neubau vonWohngebäuden einschl. Umsatzsteuer") (Reference year 2010: 100 index points; 2005: 87.8 index points) published by the German Federal Office of Statistics (DESTATIS, 2015*b*)

[2] Damage values corrected for the year 2010 based on the consumer price index for consumer products excluding food ("Verbrauchs-und Gebrauchsgüter ohne Nahrungsmittel und ohne normalerweise nicht in derWohnung gelagerte Güter") (Reference year 2010: 100 index points; 2005: 96.3 index points) published by DESTATIS (2015*a*).

2.4.4 Recovery

As far as the physical flood damage is concerned, results show that a large share of the respondents have fully recovered from flood damage at the time of the interview. Fifty-nine percent of the respondents in Osnabrück, 64% in Hersbruck and 57% in Lohmar reported that damage to their building was fully repaired about 17 to 18 months after the flood. Another 20% in Osnabrück (14% and 16% in Hersbruck and Lohmar, respectively) indicated the second best answer category on a six-point answering scale. Only 2% of the respondents in Osnabrück and Hersbruck stated that their building still showed considerable deficits, while this answer category was not chosen by households in Lohmar. Very similar findings are reported by Kienzler et al. (2015), who find that 77% of respondents affected by fluvial flooding stated a very good or good building status 13 to 18 months after the event. As far as the damage to contents is concerned, physical recovery appears to be somewhat slower. Here, only 35% of the households in Osnabrück, 49% in Hersbruck and 40% in Lohmar reported that their damaged contents were fully replaced. The second best answer category was chosen by another 12% in Osnabrück, 9% in Hersbruck and 17% in Lohmar. In line with the findings for building damage, only a minor share of 2% to 7% of the respondents reported that their contents still showed considerable deficits. Findings are again in line with Kienzler et al. (2015), who also report a slower physical recovery for contents compared with the building status for people affected by fluvial flooding. In addition, respondents were also asked whether they received financial compensation. Results show that only 21% of respondents in Osnabrück received financial compensation for the damage they had suffered. Slightly lower values were found for Hersbruck (13.5%) and Lohmar (13%). Two to ten percent of the respondents chose the "don't know/no answer" category and the rest did not receive compensation. Those who received compensation reported a mean value of EUR 7,021 (standard deviation: EUR 10,868; median: EUR 2,000) in Osnabrück and a similar mean value of EUR 7,700 in Lohmar (standard deviation: EUR 7,852; median: EUR 5,500). In Hersbruck, mean compensation is significantly higher with EUR 25,595 (standard deviation: EUR 73,923; median: EUR 3525). However, it has to be noted that this higher mean is caused by an outlier that reported a compensation of EUR 260,000. Moreover, it should be taken into account that the number of observations is very low for this specific aspect, ranging from eight in Lohmar, 15 in Hersbruck to 21 in Osnabrück and findings thus need to be carefully interpreted. The large majority of the respondents in Osnabrück (19 out of 21) received financial compensation from their insurer. Only three respondents indicated that they had received financial support from the flood relief fund of the government ("Soforthilfe"). For Hersbruck and Lohmar, this information is not available. The results furthermore show that the few respondents who received compensation evaluated the damage-compensation process mostly positively, with 57% and 14% choosing the best and second best out of five answer categories in Osnabrück. This indicates that insurance can be an effective mean to cover damage caused by heavy rain events. In Hersbruck and Lohmar, satisfaction with the compensation process was somewhat lower with 33% and 37% choosing the highest answer category, respectively. Contrary, 9.5% of the households in Osnabrück indicated the two lowest answer categories. The share of the respondents that is not satisfied with the compensation process—indicated by the two lowest answer categories—is considerably higher in Hersbruck and Lohmar with 27% and 37%, respectively. However, these findings should again be carefully interpreted given the low number of observations for this aspect.

In the present paper, recovery exclusively referred to the replacement and repairs of physical flood damage. It should be noted, though, that this is merely one aspect of recovery. In addition, floods can also have a large and more long-term impact on the psychological well-being of those affected (Lamond et al., 2015), which needs be accounted for in policies and measures that aim at supporting the recovery process of disaster stricken areas.

2.5 Conclusions

Pluvial floods are often described as the "invisible hazard", since they may occur everywhere (Houston et al., 2011). The majority of private households in all three study areas were not aware of the pluvial flood risk. The preparedness level of affected households improved considerably in the three study areas after the flood. However, raising awareness for pluvial floods remains challenging and, so far, risk management strategies in the three study areas and elsewhere are mainly focused on fluvial floods. This was particularly observed in the Hersbruck study area, where smaller previous pluvial and fluvial flood events in other parts of the city and the availability of flood maps did not seem to have an effect on the preparedness before the 2005 pluvial flood event. Thus, future risk communication and management strategies should take into account that the preparedness of private households for pluvial floods is low in most areas. The majority of households who either have experienced a flood before or had knowledge about the flood hazard see precautionary measures as an effective way to reduce pluvial flood damage. However, only very few were willing to invest in expensive building retro-fitting. Apparently, the different hazard characteristics of pluvial floods compared to fluvial floods lead to a shift in private damage mitigation strategies from costly and elaborate private precautionary measures to an effective emergency response. By comparing the pluvial flood damage in all three study areas, it seems that especially for content damage, preparedness and the implementation of emergency measures in particular, play important roles in damage mitigation. In Osnabrück, for instance, a considerably higher fraction of households received an early warning and successfully implemented emergency measures. This led to the lowest average content damage even though flood characteristics were the most severe in all of the three subsets. In line with the results by Van Ootegem et al. (2015), it can be concluded that receiving an early warning in time and knowing how to respond to this warning can effectively reduce damage caused by pluvial floods. While in all three study areas severe weather warnings with lead times of several hours were released, only a minority of households actually received the warning. Thus, not only a higher awareness and preparedness through adequate risk communication is needed, but also improved early warning systems. This includes a location specific warning, a warning chain with clear thresholds and information on suitable emergency measures, as well as an effective dissemination. The latter is constantly improved by including various media channels such as SMS, social media platforms, smartphone applications and improved websites.

The comparison between the three case studies revealed that damage caused by pluvial floods is the result of complex interactions between hazard characteristics, precaution, warning, emergency response and other influencing factors. Therefore, further research and pluvial flood damage models are needed to better understand the damaging processes as well as to improve risk analyses.

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3 | A comparative survey of the impacts of extreme rainfall in two international case studies

Summary. Flooding is assessed as the most important natural hazard in Europe, causing thousands of deaths, affecting millions of people and accounting for large economic losses in the past decade. Little is known about the damage processes associated with extreme rainfall in cities, due to a lack of accurate, comparable and consistent damage data. The objective of this study is to investigate the impacts of extreme rainfall on residential buildings and how affected households coped with these impacts in terms of precautionary and emergency actions. Analyses are based on a unique dataset of damage characteristics and a wide range of potential damage explaining variables at the household level, collected through computer-aided telephone interviews (CATI) and an online survey. Exploratory data analyses based on a total of 859 completed questionnaires in the cities of Münster (Germany) and Amsterdam (the Netherlands) revealed that the uptake of emergency measures is related to characteristics of the hazardous event. In case of high water levels, more efforts are made to reduce damage, while emergency response that aims to prevent damage is less likely to be effective. The difference in magnitude of the events in Münster and Amsterdam, in terms of rainfall intensity and water depth, is probably also the most important cause for the differences between the cities in terms of the suffered financial losses. Factors that significantly contributed to damage in at least one of the case studies are water contamination, the presence of a basement in the building and people's awareness of the upcoming event. Moreover, this study confirms conclusions by previous studies that people's experience with damaging events positively correlates with precautionary behavior. For improving future damage data acquisition, we recommend the inclusion of cell phones in a CATI survey to avoid biased sampling towards certain age groups.

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3.1 Introduction

More than 200 major flood events occurred in Europe between 1998 and 2009, causing 1126 deaths, displacement of about half a million people and around EUR 52 billion insured economic losses (European Environment Agency, 2010). These lumped statistics include various types of flooding, including fluvial floods, flash floods, and pluvial floods in urban areas that are triggered by extreme rain events overwhelming urban drainage systems. Currently, only little is known about the contributions of the different flood types and characteristic damage processes.

To better manage floods and to reduce their impacts, the European Union launched the Floods Directive in 2007 (European Commission, 2007). When implementing the directive, most of the countries concentrated on fluvial and coastal floods and neglected pluvial floods despite their damaging character (European Commission, 2016). However, recent pluvial flood events in urban dwellings in Europe and elsewhere have demonstrated that the adverse consequences of extreme rainfall must not be neglected. This includes large cities such as seen in the pluvial floods in Copenhagen in July 2011, with EUR 807 million of insured losses (Garne et al., 2013) or in Beijing, where a rainstorm in July 2012 caused an estimated total loss of over USD 1.86 billion (Wang et al., 2013), but also smaller cities such as the city of Hull, which suffered, among other towns in the UK, from severe pluvial flooding after a series of extreme rainstorms in 2007 (Coulthard and Frostick, 2010). In addition to losses caused directly by pluvial flooding, damage can also be caused by rainwater directly entering the building through roofs (Spekkers et al., 2015).

A prerequisite for an adequate management of the risks of extreme rainfall is a quantitative analysis of the hazard and its potential impacts. To quantify impacts, processes that govern damage caused by extreme rainfall have to be analyzed, understood and finally used to derive quantitative loss models. Accurate, comparable and consistent data on impacts of extreme rainfall and potentially influencing factors, gathered on the scale of flood-affected properties, serve as a good basis. While such comprehensive data sets have been collected for fluvial floods in recent years (e.g. Gissing and Blong, 2004; Thieken et al., 2005, 2016; Kreibich et al., 2007; Kienzler et al., 2015), data collection for extreme rainfall is rare and samples are much smaller (Rözer et al., 2016; Van Ootegem et al., 2015).

Two approaches to collect ex-post damage data can be distinguished. Large data sets originate from loss adjustments by insurers or from payouts of governmental disaster funds or other risk transfer schemes. Such data sets provide a complete picture of the losses of insured households and properties with regard to the total amount of losses and also their spatial as well as temporal distribution. However, these data do not contain information on damage conditions and the processes underlying damage estimates. Therefore, they are only of limited use for loss model development (e.g. Spekkers et al., 2014). In addition, loss data from risk transfer schemes, particularly from flood insurance, may be biased. Insurance data only cover households that are insured and thus not necessarily the whole affected population. Moreover, insurance contracts commonly include a deductible as well as an excess rate; i.e. the insured household has to cover small losses as well as losses which exceed the excess rate on their own. Thus, these costs have to be added to the payouts in order to receive the total loss (e.g. Thieken et al., 2006). In addition, access to damage data from risk transfer schemes and similar sources might be constrained by data privacy protection

Scientific surveys can help to overcome some of the problems associated with insurance data sets. Surveys allow the collection of detailed information on the property scale including many factors that might influence the amount and type of damage, such as hazard characteristics at the affected property, characteristics of the affected structure including property-level precautionary and emergency measures, and socio-economic variables of the affected households.

However, due to the high costs and the dependence on the willingness of affected residents to participate in the survey, only a sample of the affected population can be investigated and is hence covered by the data. Depending on the questionnaire and survey mode, this sample can be biased through an overrepresentation of certain groups (selection bias) or a cognitive bias caused by the questionnaire (response bias). In contrast to data from insurances, surveys are not necessarily restricted to residents that suffered from damage. In fact, residents that live in the affected area but did not experience damage may contribute information that is important for damage analysis and risk mitigation (Van Ootegem et al., 2015).

In the past decades, several scientific surveys have been conducted in the aftermath of severe flood events, focusing on private households in Germany (e.g. Kreibich et al., 2005; Thieken et al., 2005, 2007, 2016; Kienzler et al., 2015). Only a few surveys have been carried out to investigate the risks and damage associated with extreme rainfall. For example, Van Ootegem et al. (2015, 2018) conducted a mail survey in 2013 among pluvial flood victims in Flanders, the northern part of Belgium. People were asked to report how much damage they suffered to several parts of the building as well as the building contents. Explanatory variables were collected, such as building characteristics, behavioral indicators and socio-economic variables, to construct multivariate damage models for pluvial floods. Rözer et al. (2016) used data collected through computer-aided telephone interviews (CATI) to analyze three pluvial flood events in Germany. Rözer et al. (2016) found emergency response played a bigger role in pluvial flood damage mitigation than in fluvial floods, because of the relative low water depths associated with pluvial floods and a low risk awareness among people for this type of flooding. Poussin et al. (2015) conducted a mail survey in three regions in France to investigate how households reacted in terms of mitigation measures for different types of flooding, including pluvial flooding. They found that the effectiveness of flood mitigation measures depends on the characteristics of the flood hazard. Morss et al. (2016) conducted interviews on people's risk perception of flash floods by sending a mail survey to 1000 randomly chosen households in Boulder, Colorado, and 200 students from the University of Colorado, Boulder. Their study showed that respondents who had prepared themselves for flash floods or who perceive a higher likelihood of being killed by a flash flood were also more willing to take protective actions in response to a flash flood warning.

For this type of analysis, the risk management was found to be a valuable framework (Thieken et al., 2007; Kienzler et al., 2015; Rözer et al., 2016) . This cycle generally consists of three phases (see Figure 3.1).

1. Response and recovery: just before, during and immediately after a damaging event, residents take emergency measures to limit adverse effects of the event and start to clean-up and repair damage as soon as possible in order to regain the pre-event standard of living.

2. Risk analysis and event assessment: in order to create a sound knowledge base for risk management, a phase of risk analysis and event assessment should be performed including the investigation of the adverse consequences.

3. Disaster risk reduction: in the face of a next disaster, residents plan and implement adequate precautionary and preparatory measures that aim at preventing and mitigating risks.

In this paper, we analyze the impacts of extreme rainfall to residential buildings in the cities of Münster (Germany) and Amsterdam (the Netherlands) as well as precautionary behavior and emergency response by households, using the risk management cycle as an aid to analyze and present results. The two cities suffered from extreme rainfall in the past years, most notably

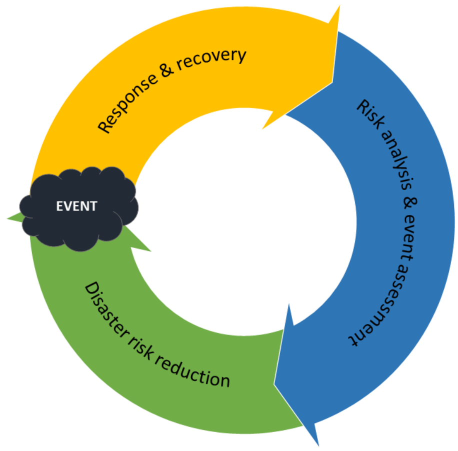

Figure 3.1: The risk management cycle used as a framework for the exploratory data analyses in this paper.

the severe weather event of 28 July 2014 that caused rainfall damage in parts of northern and central Europe. Within the risk management cycle, we focused on the following research questions in particular:

1. How did residents in Münster and Amsterdam respond to a hazardous rain event by undertaking emergency measures?
2. What is the financial damage to building structure and building content due to a hazardous rain event?
3. How does the level of precaution and other possible explanatory variables affect the height of these losses?
4. How prepared are residents in Münster and Amsterdam for extreme rainfall?
5. Does experience with previous damaging rain events affect people's precautionary behavior?

These questions were indicated as being important for flood risk management during panel discussions with professionals working for the city of Amsterdam. Similar questions were also discussed in related studies by Kienzler et al. (2015); Rözer et al. (2016).

Scientific surveys were administered among affected households in Münster and Amsterdam to collect information on self-reported financial losses caused by damage to building structure and building content as well as factors potentially influencing damage, such as hazard, building and socio-economic characteristics. A questionnaire was developed for the purpose of investigating the impacts of intense local rainfall. It has a flexible structure and is set up in open source software to make it easily adaptable and applicable to other cases.

After briefly describing the two case studies and the damage data collection campaign in the next section, we discuss the result of the case study comparison in Section 3.3. We then discuss possible methodological biases and differences between the case studies due to hazard and regional characteristics (Section 3.4). Conclusions are summarized in Section 3.5.

3.2 Data and methods

3.2.1 Case studies

Two case studies are central in this paper: the cities of Münster (Germany) and Amsterdam (the Netherlands). Both cities suffered rainfall damage caused by a synoptic weather event that occurred on 28 July 2014. The following two sections describe the case studies in detail. Key features of the two case studies are summarized in Table 3.1.

Table 3.1: Key features of the two case studies.

	Münster	**Amsterdam**
Rainfall characteristics	28 Jul 2014: 292 mm in 7 h[1] 220 mm in 1.75 h[1]	28 Jul 2014: 93 mm in 6.5 h[2] 40 mm in 1 h[2]
Dominant building style	Single-family houses[3]	Multifamily houses[4]
Building years	1950–1990 [3]	1880–1940[4]
Sewer system	80% separate system[5]	75% separate system[6]
Impervious surface	34%[7]	61%[8]
Recent flood history	No floods before 28 July 2014	Minor floods
Survey period	20 Oct 2015–26 Nov 2015	20 Jan 2016–28 Apr 2016
Investigated damage processes	Pluvial flooding	Pluvial flooding; Water intrusion through roofs
Survey mode	Computer-aided tel. interviews	Computer-aided tel. interviews; Online survey

[1] LANUV NRW (2015); [2] KNMI (2017); [3] LfStat (2017); [4] Kadaster (2013); [5] Grüning and Grimm (2015); [6] Waternet, personal communication (2017); [7] Münster (2014); [8] City of Amsterdam (2016)

Münster

On 28 July 2014, the city of Münster (population: 310 000, area: 300 km^2) and the smaller town Greven (population: 37 000, area: 140 km^2) were hit by an extreme rainfall event. The event, which exceeded a return period of 100 years, was a result of an interaction between a stationary cold front over Münster and constantly incoming hot and humid air from the east (Grüning and Grimm, 2015). Between 14:00 UTC and 21:00 UTC, a rain intensity of 292 mm in 7 hours was measured at the weather station "Hauptkläranlage", north of the city center of Münster, operated by the State Environmental Agency of North Rhine-Westphalia (LANUV NRW, 2015). At its peak, a depth of 220 mm was accumulated in 1.75 hours.

Except for the west, the whole city of Münster and all of Greven were affected by pluvial flooding. There was no flooding of a river system in that region that day. More than 7000 residential houses were damaged, and around 24 000 households were without electricity for some hours. The rail and road traffic was disrupted that day. The total damage to private households for Münster is estimated to be more than EUR 70 million (GDV, 2015). The most affected neighborhoods in Münster were located in the east of the city.

Ground elevation differences in Münster are up to 30–60 m. The percentage of impervious surfaces in the city center is around 90% and on a city-wide level 34%. Münster has a high percentage of single-family houses, built in the period of 1950–1990. There is an intensive residential use of souterrains by students. Around 80% of the city area has separate sewer systems (Grüning and Grimm, 2015). The city of Greven directly borders to the city of Münster but is part of another administrative district (i.e. Steinfurt). Greven is a small mid-sized town, with mostly small single-family houses – the earliest dating back to the 19th century.

The case study area compromises neighborhoods in Münster and Greven that were most affected (Figure 3.2), based on fire brigade data on street level provided by the cities of Münster and Greven. All streets that had at least one, for Münster, or three, for Greven, fire brigade records on 28 July 2014 were selected. This case study focuses on households that suffered from pluvial flooding, which was the scope of the EVUS project that funded the Münster survey. In the remainder of the paper, we refer to “Münster and Greven” as “Münster”.

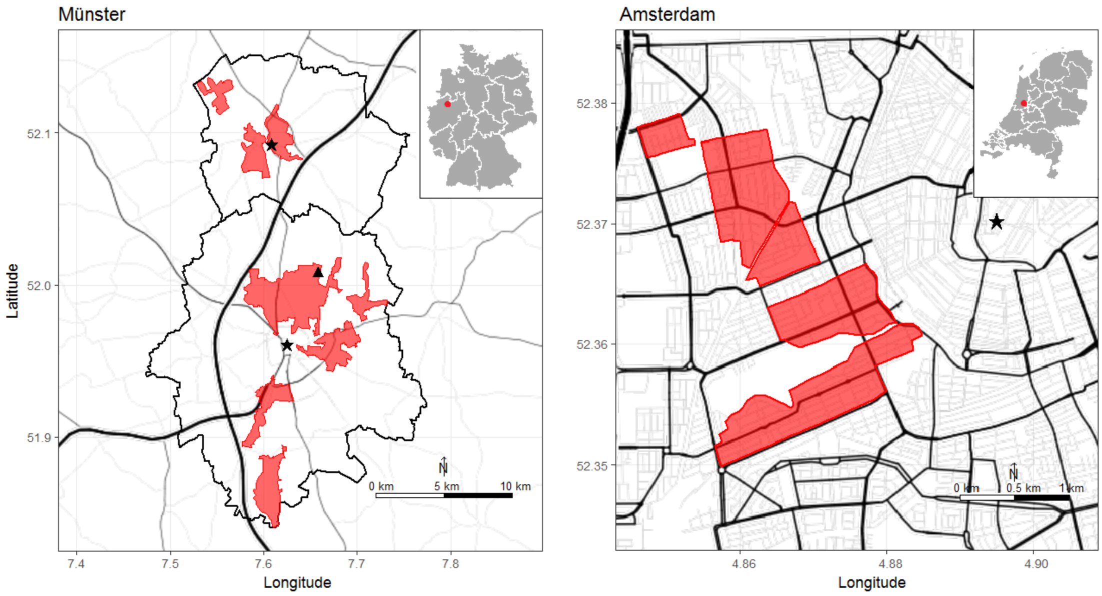

Figure 3.2: Overview map of the two case study areas. The left panel shows the cities of Münster (bottom) and Greven (top). The black triangle shows the location of the gauge ‘Hauptkläranlage’ in Münster. The right panel shows the neighbourhoods Oud-West and Oud-Zuid in Amsterdam. Sample areas are shown in red. The black stars indicate the centres of the three cities.

Amsterdam

The city of Amsterdam (population: 830 000, area: 230 km^2) was also hit by extreme rainfall on 28 July 2014. Between 07:30 UTC and 14:00 UTC, a total of 93 mm of rainfall was accumulated in 6.5 h, based on radar data from the Royal Netherlands Meteorological Institute (KNMI, 2017). A maximum hourly rain intensity of 40 mmh^{-1} was recorded between 09:15 and 10:15 UTC (i.e. 40 mm in 1 h is exceeded once every 50 years).

Parts of the highways around Amsterdam were temporarily closed for traffic due to the rainfall. Throughout the city, floods were reported, mostly in the centrally located neighborhoods Oud-West and Oud-Zuid (see Figure 3.2). Areas for the survey were based on a density analysis of fire brigade and municipal flood data of the city of Amsterdam.

The case study area is characterized by multifamily houses (i.e. apartment buildings) built in the period of 1880–1940 and mostly connected to separate sewer systems. The percentage of impervious surface areas is 61%, based on 2016 GIS data provided by the city of Amsterdam. The area is known for having many semi-basements (i.e. souterrains) which are vulnerable to flooding; an exact number on the percentage of houses with a basement could not be obtained from public data sources. The case study area is practically flat (height differences of 2–3 m). Besides pluvial flooding, we investigated cases of roof leakages in this case study, too. The survey included not only data from the 28 July 2014 event but also other smaller rain events that occurred after 2010. Since the extreme rainfall event on 28 July 2014 was most often reported by respondents (41% of all cases), we refer to this event in the event description.

3.2.2 Damage data collection procedure

To identify factors that influence damage and gain insights on coping strategies, we conducted surveys among tenants and homeowners in Münster and Amsterdam whose houses were flooded due to rainfall. In line with the work by Van Ootegem et al. (2015), the surveys were also applied to flooded households that did not suffer any damage. The member of the household with the best knowledge of the damaging event was asked to participate in the survey. Homeowners were asked to report on their damage to building content and building structure, while tenants were only asked to report on the latter in case they had detailed knowledge about the structural damage of the building. We aimed for a minimum of 300 completed interviews per case study to avoid small subsamples (e.g. groups of respondents that take a certain precautionary measure).

A questionnaire was developed for the collection of damage data associated with extreme rainfall events, building upon an existing questionnaire for fluvial flooding (Thieken et al., 2005; Kreibich et al., 2005). River or groundwater flooding are not addressed in this questionnaire. The questionnaire was organized in six thematic groups, containing 82 mainly closed questions. The questionnaire acquires information on financial losses caused by damage to building structure and content, hazard and building characteristics, people's precautionary behavior and emergency response. A more detailed description of the questionnaire design is given in Appendix 3.A.1.

In Amsterdam, we conducted computer-aided telephone interviews and an online survey. Samples were randomly drawn from a database of landline and cell-phone numbers (2269 households) held by EDM, a customer data analytics company, for the selected case study area. A team of trained students carried out the CATI in the period of 20 January to 28 April 2016. We conducted an online survey among 7000 households for which we were not able to retrieve a phone number. Survey participants who suffered damage from multiple rain events were asked to focus on the most recent event. In case participants suffered from a rain event after 2010 other than the one on 28 July 2014, they were asked to report on this event. Therefore, the analyses in this study do not exclusively refer to the extreme rainfall events on 28 July 2014, but impacts of extreme rainfall in general. For Amsterdam, the entire database of survey responses is available under Creative Commons Attribution-NonCommercial license (CC BY-NC) and can be downloaded from the DANS archive (Spekkers, 2016).

In Münster, a CATI among tenants and homeowners was conducted by *explorare*, an independent market research institute. Samples were drawn from the Deutsche Post address database (7445 households) for the affected streets. The generic questionnaire was adapted for this case study to be consistent with existing flood damage databases. More details on the survey modes of the Münster and Amsterdam case studies and the sampling procedures are given in Appendix 3.A.2. Some post-processing activities were performed on the collected data. Checks were performed to correct or remove implausible inputs, for example, by comparing reported water levels inside and outside the house and by comparing reported floor areas with building footprint. Responses to open questions (e.g. the "Other" field of the question "How did water get into your house?") were manually categorized. First, open answers were categorized using existing answer categories wherever possible. If the open answer did not fit in any of existing categories, but was given by several respondents, a new category was added. Otherwise the answer was set to "Other".

3.2.3 Data analyses

Table 3.2 presents an overview of the collected data used for analyses in this paper. Similar to the papers by Thieken et al. (2007), Kienzler et al. (2015) and Rözer et al. (2016), the risk management cycle (Figure 3.1) is used as a framework for the data analyses and the presentation of the results. In the present study we did not cover the topic of recovery, because this would require repeated surveys over a period of time.

Response is here defined as the efforts to minimize the damage created by a disaster by taking emergency measures just before, during or immediately after the event. This topic covers items labeled "Response" in Table 3.2. People's response was analyzed by means of a frequency analysis of the emergency measures people took. A few emergency measures were only asked in one of the two case studies. In the present paper, we only report on emergency measures that were considered in both case studies.

Table 3.2: Items of the questionnaires that were used in this paper.

Item	**Measurement scale[1], unit and labels**	**Risk management cycle**
	Hazard characteristics	
Water depth in basement	r: m	Risk analysis
Water depth at ground level	r: m	Risk analysis
Contaminated water	n: No | Yes	Risk analysis
Entry point of water	n: How water got into the house	Risk analysis
	Building information	
Presence of a basement	n: No | Yes	Risk analysis
Floor area	r: m^2	
Building type	n: Detached | Semi-detached | Terraced | Multi-family	
	Damage information	
Damage to building structure	r: EUR	Risk analysis
Damage to building content	r: EUR	Risk analysis
	Preparedness	
Flood experience	r: Number of previous flood events	Disaster risk reduction
Precautionary measures	n: Type of precautionary measures implemented before the event, implemented after the event and planned within six months from interview date	Disaster risk reduction
Aware of upcoming rain event	n: No | Yes	Risk analysis
Respondent was at home	n: No | Yes	Risk analysis
Emergency measures	n: Type of emergency measures implemented	Response
	Socio-economic variables	
Age of the respondent	r: Number of years	
Gender	n: Female | Male	
Education	o: Highest degree of education obtained	
Household size	r: Number of persons living in the household	
Ownership structure	n: Homeowner | Tenant	

[1] r = ratio, o = ordinal, n = nominal

Risk analysis and event assessment, in this paper, relates to the analysis of damage characteristics and the factors influencing damage. This topic covers items labeled "Risk analysis" in Table 3.2. We distinguished between damage to building structure and building content as well as the total damage. Building structure is here defined as everything permanently connected to the building, such as building walls and ceiling, permanent flooring and infrastructure. Building contents are portable goods and semi-permanent objects, such as furnishing, curtains and carpets. Total damage was calculated by summing building structure damage and building content damage for the records where both values are available, including reported zero values. We analyzed the effect of the following binary variables on damage:

- water contamination by sewage, chemicals, oil or gas;
- presence of a basement;
- if respondent was at home;
- respondent's awareness of the upcoming severe weather event;
- respondent's experience with water intrusion;
- if respondent took at least one precautionary measure.

We performed a median ratio test to analyze the significance of these variables, i.e. by comparing the median damage in the subset of the data for which the binary variable is *true* with the median damage in the subset of the data for which the binary variable is *false*. For this purpose, we estimated the confidence intervals of the difference between the medians using a bootstrapping method with 10 000 bootstrap samples (e.g. Haukoos and Lewis, 2005).

Disaster risk reduction is here defined as a set of actions that is taken as precautionary measures in the face of a potential disaster and refers to items labeled "Disaster risk reduction" in Table 3.2. We investigated the number and the type of precautionary measures respondents took as well as when respondents implemented these measures. A few precautionary measures were excluded from the analysis because they were only investigated in one of the two case studies. The correlation between people's preparedness and their experience with previous damaging rain events was determined by comparing the mean number of precautionary measures people have taken before the event in groups of respondents with and without previous flood experience. Experience is here defined as having at least one experience with a damaging rain event, independent of the severity and the recency of earlier events. A two-sided t-test was performed to test whether means are significantly different.

3.3 Results

3.3.1 Summary statistics of the data set

A total of 859 questionnaires were completed, including 510 for Münster and surroundings and 349 for Amsterdam. The Münster data set contains 447 completed questionnaires from the city of Münster and 63 from the neighboring town of Greven. Basic statistics are summarized in Table 3.3. The response rate was calculated according to Response Rate 1 (*RR1*) in AAPOR (2015) by dividing the number of completed questionnaires by the number of contacted households. In Amsterdam, the response to the CATI survey (9.3%) was higher than the online survey (2.0%). The CATI survey of Münster was in between with a response rate of 6.9%. In the CATI survey, multiple call attempts were made to obtain a completed questionnaire, whereas for the online survey we only sent out a survey invitation letter once. The interviews

Table 3.3: Basic statistics of the data sets. City-level census data are obtained from the databases of LfStat (2017) and Statistics Netherlands (2017), for Münster and Amsterdam respectively. Characteristics of people relate to persons older than 15 years.

	Münster		**Amsterdam**		
	Phone sample	Census data	Phone sample	Online sample	Census data
Survey characteristics					
Number of completed questionnaires	510		210	139	
Number of contacted households	7445		2269	7000	
Response rate [%]	6.9		9.3	2.0	
Mean interview time in minutes	29		21	21	
Demographic characteristics					
Mean age of the respondent	64	45	56	54	43
Female/male ratio	1.3	1.1	0.8	0.8	1.0
People with Master degree or higher [%]	37	20	50	55	38
Mean household size	2.3	2.2	2.3	2.3	1.8
Mean floor area [m^2]	130	95	110	100	-
Percentage of homeowners	80	42	66	63	39
Percentage of single-family houses	33	32	19	16	-

averaged eight minutes longer in Münster than Amsterdam mainly because of a difference in the length of the questionnaires.

Response bias was checked by comparing demographic indicators between response sample and census averages. Respondents in both cities are relatively old, highly educated and more often homeowners, compared to city-level averages (Table 3.3). There can be several explanations for this. In the Münster survey, only landlines phone numbers were available. Due to the increasing use of cell phones, elderly people may tend to be overrepresented in a landline-only sample, as argued by Kienzler et al. (2015). In the Amsterdam survey, selected areas affected by flooding were more expensive, and the sample is therefore not representative for the city as a whole.

Unpublished research by the second author, based on data from a previous study (Rözer et al., 2016), shows that demographic variables, similar to those listed in Table 3.3, do not correlate with damage. The exception is the variable "Percentage of homeowners", which shows a weak positive correlation with damage. We therefore expect that damage amounts reported in this study may be overestimated because of the response bias. More details on a possible response bias are given in Section 3.4.

3.3.2 Frequency analysis of emergency response data

A total of 39% of the respondents in Amsterdam and 71% of the respondents in Münster have implemented at least one emergency measure before or during the event out of the 11 emergency measures compared in this study. Compared to similar studies by Rözer et al. (2016) for pluvial floods and Kienzler et al. (2015) for fluvial floods, the percentage for Münster is high and the percentage for Amsterdam is among the lowest. For the frequency analysis all observations including missing data were considered. Therefore, the results have to be interpreted with caution as a large number of respondents in Amsterdam did not answer this question (43-45%; see also Section 3.4.1 - *Questionnaire structure*).

Figure 3.3 shows an overview of the implemented emergency measures in the two cities. For 8 out of 11 emergency measures, the percentage of respondents who implemented emergency

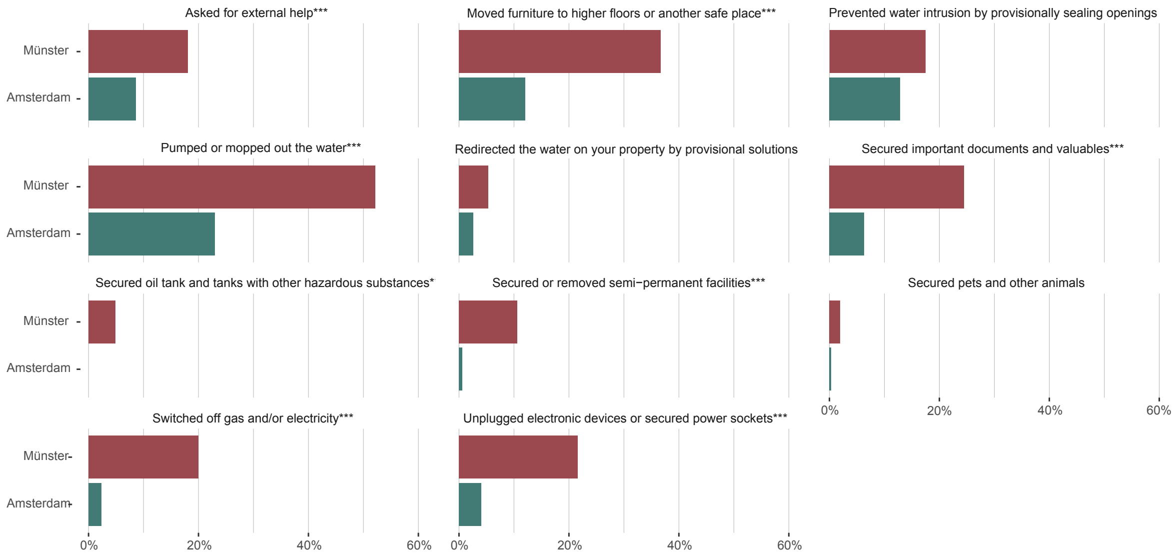

Figure 3.3: Percentage of respondents undertaking emergency measures. Only emergency measures are shown that were asked in both cities. A significant difference between proportions is denoted as follows: $* = p < 0.05$, $** = p < 0.01$, $*** = p < 0.001$.

measures is significantly higher in Münster than in Amsterdam on a 0.001 significance level. “Pumping or mopping out the water” is in both cities by far the most frequently implemented measure (Münster 52%, Amsterdam 23%). The measure “Moving furniture to higher floors” ranks second in Münster (37%) and third in Amsterdam (12%). These findings are in line with studies by Rözer et al. (2016); Kienzler et al. (2015), where the two above-mentioned emergency measures are also among the three most frequently implemented measures. A survey among pluvial flood affected households in Flanders, Belgium, revealed a similar percentage for "Moving furniture to higher floors" as in Amsterdam (Van Ootegem et al., 2015).

Unlike the measures "Pumping or mopping out the water" and "Moving furniture to higher floors", other measures differ considerably in popularity between the two cities. For example, the measure "Provisionally sealing openings" ranked second in Amsterdam (13%), but was one of the least popular in Münster (18%). The differences in emergency response can partly be explained by the differences in event magnitude. Some measures are more sensible to take than others depending on the flood depth, as is discussed in more detail in Section 3.4.2 - *Causes of differences in emergency response.*

Table 3.4: Number of respondents providing loss information.

	Damage data	**Missing values**	**Zero damage**
Münster (n = 510)			
Structure damage	340 (67%)	170 (33%)	33 (6%)
Content damage	328 (64%)	182 (36%)	41 (8%)
Total damage	274 (54%)	236 (46%)	23 (5%)
Amsterdam (n = 349)			
Structure damage	294 (84%)	55 (16%)	91 (26%)
Content damage	325 (93%)	24 (7%)	215 (62%)
Total damage	282 (81%)	67 (19%)	58 (17%)

3.3.3 Risk analysis and event assessment

A total of 67% of the respondents in Münster and 84% of the respondents in Amsterdam reported on structural damage to the building they live in, which includes reports of zero damage (Table 3.4). A total of 64% of respondents in Münster and 93% in Amsterdam could state their damage to building contents. In the Amsterdam sample, people reported a high number of zero losses for content damage (215 out of 325 records). A similar result was found by Van Ootegem et al. (2015) who argue that these zero damages stem from the fact that "it is possible that people are able to remove the water immediately before/during the flood or they are able to protect their belongings in some way (for instance by moving them to another place)". The number of zero values is limited in the Münster sample. Since water depths in Münster were a few decimeters high, which suggests that people were not able to remove water or protect their contents effectively.

Figure 3.4 shows the distribution of the total damage (top panel), the building structure damage (middle panel) and building content damage (bottom panel) of the two data sets. There is a large variation in the loss amounts reported by respondents, ranging from tens of Euros to hundreds of thousands of Euros. Based on a comparison of the medians of the distributions, significantly higher amounts were observed in Münster than in Amsterdam; the median of the total damage is an order of magnitude larger in Münster (EUR 10 500) than in Amsterdam (EUR 1200).

The damage distributions of Münster, especially for structural building damage, are less symmetrical than those of Amsterdam and show higher peak densities. A possible cause that can explain these differences is the difference in reported water depths between the cities (Table 3.5), which is discussed in Section 3.4.2 - *Causes of differences in financial losses*. The asymmetry in the Münster data set may indicate the presence of atypical extreme observations, as discussed in more detail in Section 3.4.2 - *Causes of differences in financial losses*.

Figure 3.5 shows pathways for rainwater entering buildings as reported by respondents. In Münster, 83% of the total damage was caused by water entering the house through toilets, sinks, drains, basement entrances, doors and other openings at ground level. In Amsterdam, only 39% of the total damage was associated with these pathways. This can be partly explained by differences in the sampling strategy between Münster and Amsterdam: in Münster cases with roof leakages were only considered when the respective household had suffered at the same time from pluvial floods, while the Amsterdam sample contains cases with roof leakage only. In Amsterdam 19% of the total damage was caused by leaking roofs. The remaining difference is probably caused by the difference in the severity of the two events (see Table 3.1), combined with differences in building topology between cities, but this hypothesis could not be tested based on the available data.

Table 3.5: Reported water depths and contamination. Median and mean are based on non-zero values of the water depth.

	Münster	**Amsterdam**
Water depth in basement		
Median [m]	0.35	0.05
Mean [m]	0.49	0.16
Water depth at ground level		
Median [m]	0.20	0.02
Mean [m]	0.57	0.05
Percentage of cases with contaminated water	22	16

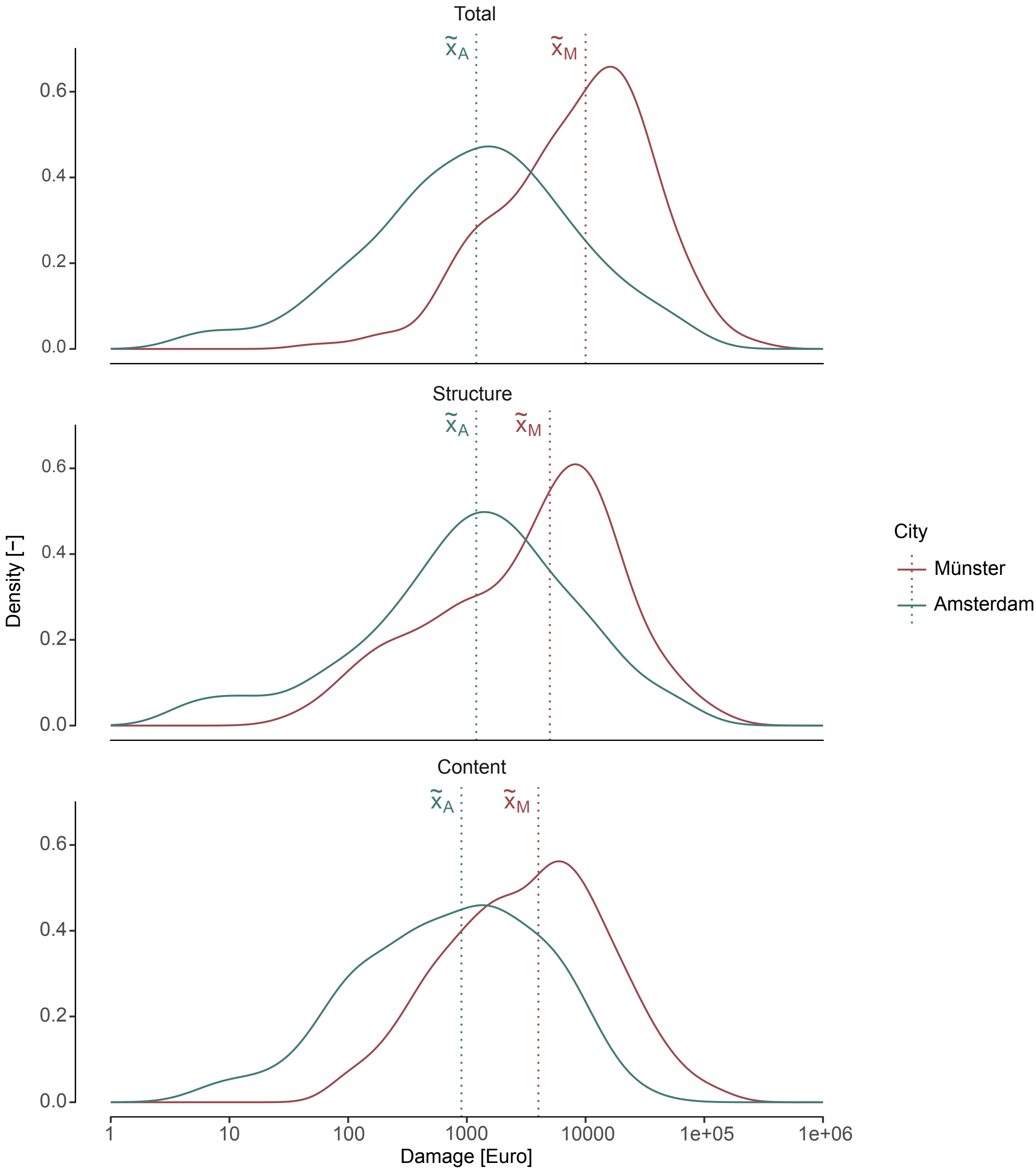

Figure 3.4: Kernel density function of the total damage (top), the building structure damage (middle) and building content damage (bottom), for Amsterdam (blue) and Münster (green). Zero values are excluded in these graphs. The vertical dashed lines represent the median of the distribution. The difference in medians ($= |x_M - x_A|$) is significant in all three plots ($p < 0.001$).

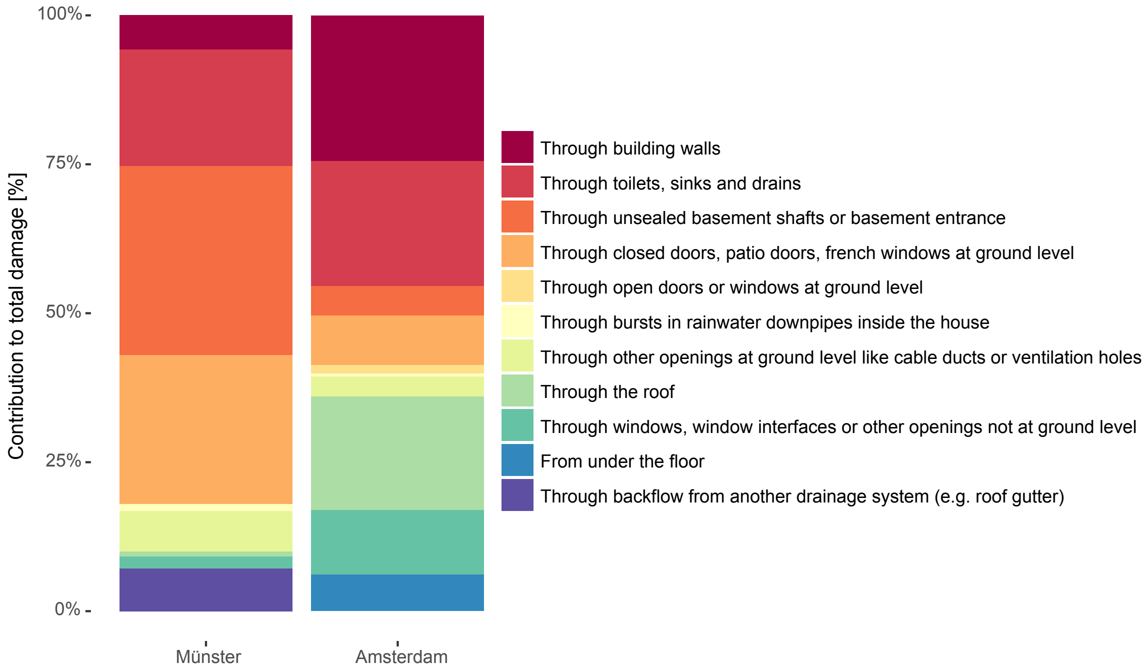

Figure 3.5: The different ways water entered a house and their relative contribution to the total damage (of all data). Damage was assigned to the pathways as follows: if a respondent only reported one pathway then the damage amount was completely assigned to that pathway. If two or more pathways were reported at the same time, then the damage amount was equally divided over these pathways.

A number of explanatory variables for damage were investigated in this study (Fig. 3.6). For Münster, we found a significant difference between respondents who reported contaminated water and those who did not, in terms of median damage. Contaminated flood water positively correlated with the median damage. No significant correlation was found for Amsterdam because the number of respondents reporting contaminated water was low (Table 3.5). In Amsterdam, the presence of a basement significantly affected the median damage with a factor 2.2. Since less than 2% of the respondents in Münster did not report a basement, more data are needed to be conclusive about the significance of this variable for this city. No significant correlations were found between median damage and the variables "Experience with water intrusion" and "Took precautionary measures". Awareness correlates positively with median damage for Münster. More research is needed to study the causality of these relationships.

3.3.4 Disaster risk reduction

Significantly more respondents took precautionary measures in Münster compared to Amsterdam (Fig. 3.7). For example, the measure "Installing a flood water pump", is taken around six times more frequently in Münster than in Amsterdam. The exception is the measure "Adapting the building structure", which is taken more frequently in Amsterdam. This is because in Amsterdam, unlike Münster, we also investigated roof leakages, and improvements to the roof were considered building adaptation.

The list of the five most popular precautionary measures of both case studies contain the same measures, but not in same order: "Requesting information about precautionary

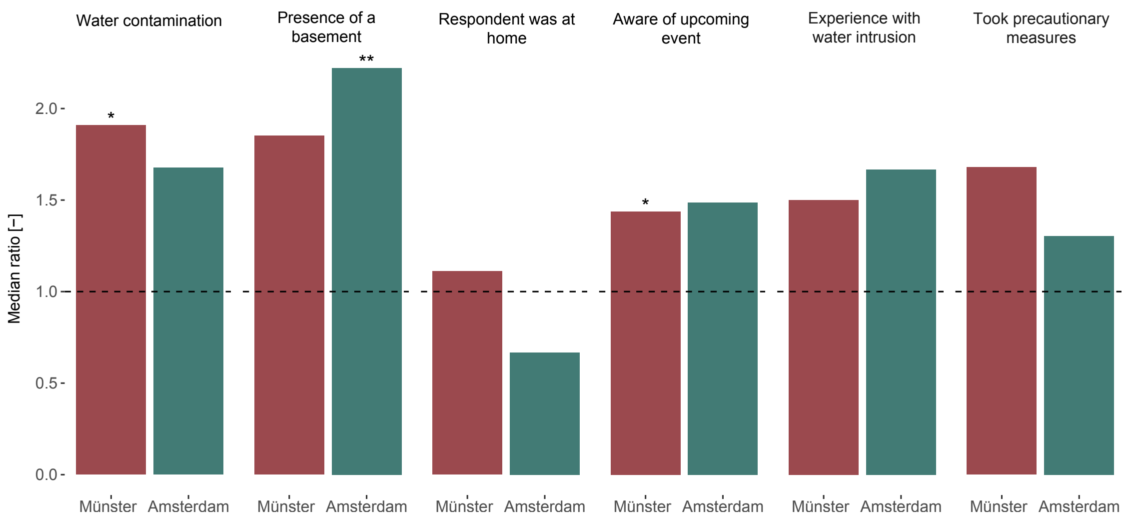

Figure 3.6: The effect of water contamination, presence of a basement in the building, presence of the respondent during the event, respondent's awareness of the upcoming rain event, experience with water intrusion and precaution on the total damage (N = 274 (Münster) and N = 282 (Amsterdam)). Damage is expressed as the ratio between the median damage in the group of respondents where variable value is *true* and the median damage in the group of respondents where variable value is *false*. A median ratio above 1 means a positive correlation and below 1 means a negative correlation. A significant difference between medians, based on a bootstrapping method with 10 000 bootstrap samples, is denoted as follows: $* = p < 0.05$, $** = p < 0.01$, $*** = p < 0.001$.

measures", "Installing a flood water pump", "Avoid expensive furnishing on the floor at risk", "Store low-value goods on floor at risk" and "Adapting the building structure" are frequently reported by respondents in the both cities. Apart from "Adapting the building structure" these are measures that can be implemented at relatively low or medium costs (Rözer et al., 2016).

Results show that respondents' actions were mostly reactive: many respondents implemented precautionary measures after the event. An exception is the measure "Installing a water pump". The reactive approach is also confirmed by Figure 3.8, which shows that respondents who have experienced water intrusion before take 1.5 to 1.7 times more precautionary measures than respondents with no experience. This is in line with studies by Kreibich et al. (2005), Bubeck, Botzen, Kreibich and Aerts (2012) and Kienzler et al. (2015).

Figure 3.8 also shows that the relative increase in uptake of precautionary measures between groups with and without experience with water intrusion seem to be independent from the number of measures implemented, as well as from the fraction of households with experience. While the majority of households in the Amsterdam dataset had experience with water intrusion (83%), the number of implemented measures was relative low, with less than one measure on average per household. In Münster, only 21% of the households stated to have experience with water intrusion, but implemented on average 2.3 measures. In Section 3.4.2 - *Causes of differences in precautionary behavior* we discuss possible explanations for the difference between cities in uptake of precautionary measures.

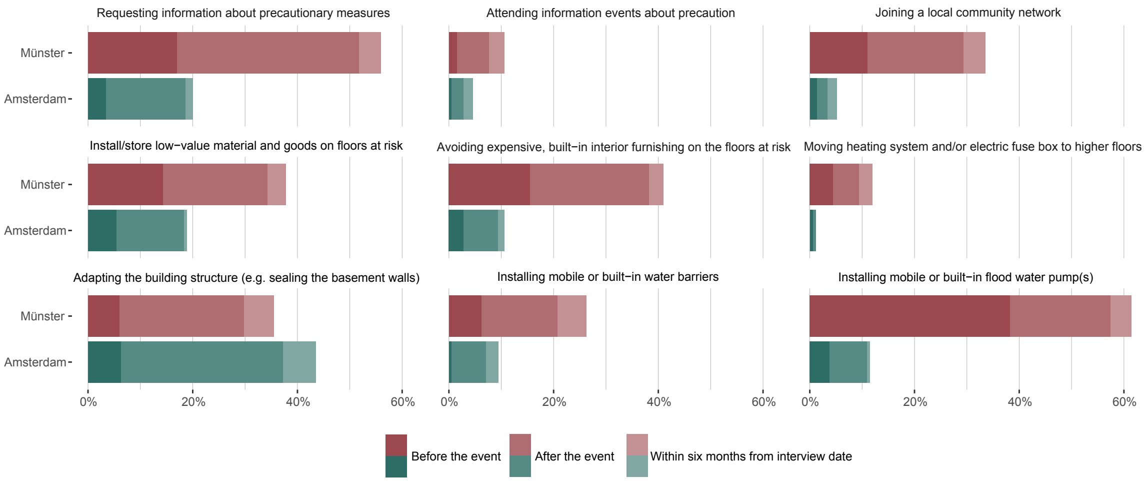

Figure 3.7: Percentage of respondents undertaking precautionary measures: before the event (blue), after the event (purple) or planned to be implemented within six months from interview date (green). Only precautionary measures are shown that were asked in both cities.

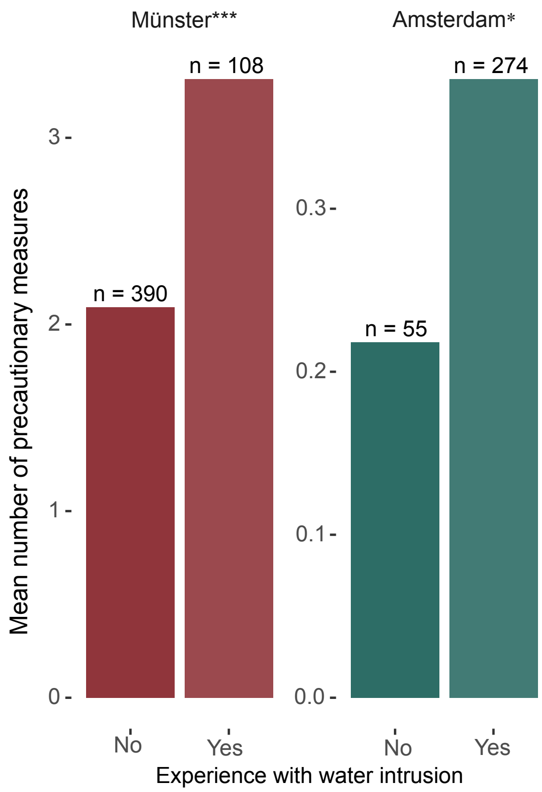

Figure 3.8: Mean number of precautionary measures against people's experience with water intrusion. A significant difference, based on two-sided t-test, between means is denoted as follows: $* = p < 0.05$, $** = p < 0.01$, $*** = p < 0.001$.

3.4 Discussion and recommendations

The results shown in Section 3.3 reveal considerable differences between the two cities in terms of emergency response (Figure 3.3), financial losses (Figure 3.4) and people's level of precaution (Figure 3.7), with generally higher losses and uptake of measures in Münster compared to Amsterdam. There are several underlying effects that may cause variations. These include methodological biases as well as differences in case study characteristics, i.e. differences in the magnitude of the events in terms of rainfall intensity and recorded water depth and regional effects such as differences in the socio-economics and building topology (Table 3.3). In this section, the observed differences are critically evaluated in terms of possible methodological biases and differences between case studies to derive more universal coherences. Moreover, we make recommendations for future surveys on the topic of damage data collection.

3.4.1 Methodological biases

As described in Section 3.2.2, the Münster and Amsterdam surveys are based on one generic questionnaire, which was adapted independently to the case studies. The main differences between the two surveys are related to the survey delivery mode and questionnaire structure.

Survey delivery mode

In Münster a single-mode CATI survey was conducted, while in Amsterdam a combination of a CATI and an online survey was used. Although there are many studies investigating survey mode effects, i.e. the possible sources of differences in survey outcomes such as selection bias, the effect of a particular mode on the survey outcome is not yet fully understood (Couper, 2011).

Demographics of respondent groups can be compared between the samples of different survey modes to check whether the choice of the survey mode has affected the representativeness of the sample (Link and Mokdad, 2006). For Amsterdam, we found only minor differences in the demographics between CATI and online survey, with a similar over-representation of older and higher-educated respondents compared to census data, as shown in Table 3.3. We therefore conclude that the choice of survey mode does not influence population representation in the samples, i.e. Münster CATI sample, Amsterdam CATI sample and Amsterdam online sample.

The bias towards older and higher-educated respondents could not have been avoided by the choice of survey mode. This bias is particularly large for the Münster sample where only landline phones were contacted. Response bias in surveys that are based on landline samples only are a well-known challenge in modern survey research. Dillman (2014) argues that because of the decreasing numbers of landline phones and accessibility to online surveys (i.e. internet connection), it becomes increasingly difficult to obtain a representative sample using a single-mode survey. A combination of a CATI with landline and cell-phone numbers and an online survey probably brought the mean age of the respondents in Amsterdam closer to census data. Because of the small differences between the telephone and online samples in Amsterdam, we assume that by including cell-phone numbers in the sample we improved the survey coverage.

Questionnaire structure

Modifications to the questionnaire structure (i.e. wording, sequencing, response format) can significantly bias survey outcomes (Couper, 2011; Bergman et al., 1994; Porst, 2014, e.g.). In the context of the present study, an important difference between the surveys (i.e. Münster CATI, Amsterdam CATI and Amsterdam online survey) is the response format of questions related to precautionary and emergency measures. These items were designed as closed questions in the Münster CATI and the Amsterdam online survey, i.e. each measure was individually presented to the respondent. In the Amsterdam CATI, a semi-closed format was chosen. While testing the Amsterdam CATI, test respondents reported to have had difficulties with focusing on closed questions that contain many sub-items, which was particularly the case with the question on precautionary measures (18 sub-items). We therefore decided to group similar kind of precautionary measures (in groups of around 3–4 items) and asked first a closed question about whether they took measures of this class. Then, clarifying questions were asked to make sure the correct precautionary measures within the group were selected. In case of doubt, the interviewer explicitly went through all items and double-checked with the respondent. However, after analyzing the collected data, we found that the closed question format in the online survey resulted in a significantly higher percentage of respondents who stated to have implemented one or more precautionary measures compared to the semi-closed format in the CATI (online survey: 34%; CATI: 15%; $p < 0.001$). The same is true for the average number of implemented measures (online survey: 0.6; CATI 0.2; $p < 0.001$). Nevertheless, these values are much smaller than the values found for the Münster survey; i.e. 64% of the respondents implemented one or more precautionary measures with an average of 2.3 measures. We can therefore conclude that besides the evident methodological bias, the level of private precaution is considerably higher in Münster compared to Amsterdam.

For the question items on emergency measures in Amsterdam, where we used a closed response format in both the CATI and the online survey, we did not find a significant difference between the two samples in terms of emergency response. However, considerably more respondents in Amsterdam did not answer this question (online survey: 45%; CATI: 43%) compared to Münster (0.4%). This was probably caused by the fact that in Amsterdam we coded a filter question (i.e. "Did you or another person in your household take any emergency measures as an immediate reaction to the rain event?") that allowed respondents to skip the question on emergency measures in case they did not implement any emergency measures or had no information about it. We presume that people were unfamiliar with the term "emergency measures" (or its Dutch translation "noodmaatregelen") and therefore skipped the question ("No answer") or answered "No" because the emergency measure(s) they applied where not perceived as such. Because of the high number of missing values, the absolute differences between the case studies should be interpreted with caution, but we can still compare the ranks of emergency measures, which will be discussed in the next section. Possible solutions to avoid missing values for this question in a future survey are given in Section 3.4.3.

3.4.2 Results associated with hazard and regional characteristics

Taking into account the methodological biases as discussed in Section 3.4.1, differences in the results between Münster and Amsterdam are also caused by differences in hazard and regional characteristics of the case studies. It is necessary to determine to what extent these hazard and regional characteristics play a role to better understand the factors that contribute to damage due to extreme rainfall.

Causes of differences in precautionary behaviour

Respondents in Münster implemented more precautionary measures compared to respondents in Amsterdam (Figure 3.7). This cannot be explained by the magnitude of the studied event, because there was a high uptake of precautionary measures in Münster before the event as well as after. Another explanation is the relation we found between the mean number of precautionary measures and flood experience (Figure 3.8), which was also found by other researchers (Kreibich et al., 2005; Bubeck, Botzen, Kreibich and Aerts, 2012; Kienzler et al., 2015), but this cannot explain the absolute difference in precaution between the cities, because flood experience results in 1.5 to 1.7 times more precautionary measures, while the mean number of implemented precautionary measures was about one magnitude higher in Münster compared to Amsterdam (see Section 3.3.4).

The absolute difference in uptake of precautionary measures may be caused by cultural- and/or language-specific differences in how respondents in Münster and Amsterdam perceive risk. Based on a study in Switzerland, Siegrist and Gutscher (2006) found German-speaking regions to have a significantly lower perception of flood risk compared to French-speaking regions. They also found, that people in German-speaking regions underestimated their flood risk, while people in French-speaking regions overestimated their flood risk compared to expert judgements. However, the relationship between risk perception and precautionary behaviour is subject to current research and not yet well understood. While few studies found a significant correlation between risk perception and precautionary behaviour (i.e. Grothmann and Reusswig, 2006), a large number of studies could not find such a relationship (see Bubeck, Botzen, Kreibich and Aerts, 2012, for an overview). We recommend to include question items on risk perception in a future survey as it may explain the level of precaution, and thus also indirectly damage.

Causes of differences in emergency response

The difference in emergency response between the case studies can to some extent be explained by the magnitude of the event in terms of reported water depths (Table 3.5).If we compare the rankings of the emergency measures between the two case studies, we can conclude the following. The most popular emergency measures were implemented in both cases (i.e. “Pumping or mopping out the water” and “Moving furniture to higher floors”) and, thus, are implemented irrespectively of the water depth. Other measures were mostly applied in case of large water depths (i.e. “Switching off gas and electricity”) or in case of small water depths (i.e. “Provisionally sealing openings”). Thus, the relative small water depths in Amsterdam not only reduced the overall necessity of taking emergency actions; they also make some measures more sensible to take than others. Rözer et al. (2016) found a similar effect: in case studies with small water depths, people focus more on emergency measures that have the goal to keep the water out (e.g. sealing openings), rather than reducing the damage after water has already entered the building (e.g. securing or moving semi-permanent facilities).

Causes of differences in financial losses

Significantly larger damage amounts were reported in Münster compared to Amsterdam, as shown in Figure 3.4. With only two case studies, it is difficult to quantify the factors that explain the variability of damage between case studies. Nevertheless, possible factors can be discussed on a qualitative level. Following the conceptual model for building damage proposed by Thieken et al. (2005), we can roughly distinguish between variables that relate on the impact to the structure (i.e. hydrological load and contamination) and the resistance of the structure (i.e. permanent resistance and temporal resistance). We expect that the Münster and Amsterdam case were mostly different because of the impacts on structures. The hydrological load in terms of water depths was much larger in Münster than in Amsterdam. Although there are differences in building types between cities (Table 3.3), we believe that differences in resistance are minor or slightly in favor of Münster, given the high uptake of emergency and precautionary measures (Figures 3.3 and 3.7).

In Amsterdam the damage distribution is more symmetrical on a logarithmic scale, while the damage distribution is negatively skewed for Münster. Generally, flood damage data follows a lognormal distribution (Zhai et al., 2005), and as a consequence the density function would appear symmetrical on a logarithmic scale, but, in case of atypical extreme observations, standard distributions such as the lognormal are unable to capture the data well (Balasooriya and Low, 2008). The asymmetry may indicate that the Münster sample contains some exceptional losses that are caused by different damage mechanisms than the bulk of the data. This could be a topic for further research.

3.4.3 Recommendations for rainfall damage surveys

Applying a survey in different countries or regions, as done in this study, is challenging. To make survey outcomes comparable, and thus to avoid methodological biases, surveys should to a large extent share the same response format, survey delivery mode, sampling techniques and questionnaire design (Bird, 2009). On the other hand, a survey should also be able to capture regional features, for example, in our case country-specific building topologies, and thus it is unavoidable to introduce some differences in the set-up between surveys of different case studies.

Some of the methodological biases we encountered in our survey could have been avoided, while others are more difficult to address. For example, we sampled only landline phone numbers in the Münster CATI. Including cell-phones in the sample can increase the representativeness of the sample as shown for the case of Amsterdam and other studies (e.g. Busse and Fuchs, 2012), but this is not possible for countries where cell-phone phones are not registered at an address (i.e. in Germany). The present study also highlighted certain issues with respect to the choice of response format for some of the questions (e.g. items on precautionary measures). A helpful tool to reduce these and other methodological issues in questionnaires is to use the template proposed by Bird (2009), who listed minimum requirements on methodological details of a questionnaire to allow comparison between case studies in natural hazard sciences. Another issue relates to the use of filter questions. A sparse use of filter questions can generate an unnecessarily long questionnaire that comes with fatigue effects and high drop out rates. However, a wrong answer to a filter question by mistake may lead to respondents skipping a block of questions, resulting in an increased number of missing observations (see Section 3.4.1 - *Questionnaire structure*). A possible way to avoid this, is to make use of validation questions to cross-check answers to important questions.

We recommend the use of the same IT infrastructure in all case studies, i.e. the same survey software and a shared data repository. This not only increases the comparability between studies, it also makes data analyses easier and less prone to errors. In Appendix 3.A.1, the LimeSurvey-coded questionnaire used in Amsterdam is presented as an example of such an infrastructure.

3.5 Conclusions

In this paper we investigated the impacts of extreme rainfall to residential buildings in the cities of Münster and Amsterdam as well as precautionary behavior and emergency response by households. Scientific surveys were conducted among affected residents in Münster and Amsterdam to collect information on self-reported financial losses, caused by damage to building structure and building content as well as factors influencing damage, such as hazard, building and socio-economic characteristics. The paper presents an open source, flexible questionnaire tool that is specific to the impacts of intense local rainfall events and can easily be adapted to international case studies.

A total of 510 questionnaires in Münster and 349 in Amsterdam were completed. Reported damage varied from tens of Euros to hundreds of thousands of Euros. The median damage was an order of magnitude larger in Münster (EUR 10 500) than in Amsterdam (EUR 1200). The mean water depths were a lot higher in Münster (0.49–0.57 m) than in Amsterdam (0.05–0.16 m). From 16 to 22% of the respondents reported water contamination by sewage, chemicals, oil or gas.

Exploratory data analyses revealed that the types of implemented emergency measures are likely to be associated with the hazard characteristics of the event, such as the water level. The Münster case, with higher reported water levels than in Amsterdam, shows a preference for emergency measures to reduce damage, such as unplugging electronic devices, switching off electricity and securing semi-permanent facilities, while in Amsterdam, with only minor water levels, people responded by undertaking emergency measures to prevent damage, such as provisionally sealing openings. The same types of emergency measures were preferred in both cases and are independent of the water levels: moving furniture to higher floors and pumping out the water.

The difference in magnitude of the events in Münster and Amsterdam is probably also the most important cause for the differences between the cities in terms of the suffered financial losses; in Münster significantly higher damage amounts were reported compared to Amsterdam, including some exceptionally high losses. Additionally, the low number of observations with no damage in Münster compared to Amsterdam shows that in Münster people were unable to prevent damage, likely due to high water levels. Within the case studies a large variation in damage was also found. Factors that are significantly associated with damage are the water contamination, the presence of a basement in the building and people's awareness of the upcoming weather event.

This study confirms the conclusions of other studies that people's previous experience with adverse events positively correlates with precautionary behavior. However, experience cannot explain the considerably higher uptake of precautionary measures observed in Münster compared to Amsterdam. We recommend that a future survey should investigate the extent to which risk perception of extreme rainfall can explain people's precautionary behavior.

3.A Supporting Information (SI)

3.A.1 SI Questionnaire

Questionnaire design criteria

We set the following requirements prior to the development of the questionnaire:

- The main objective of the questionnaire should be to characterize damage to residential buildings as a direct result of a rain event, i.e. pluvial flooding and rainwater entering the house through roofs and facades.
- The damage assessment should distinguish between the assessment of financial damage to building structure and building content; questions related to social and physical vulnerability, such as human health, will not be part of the questionnaire as this requires a completely different questionnaire design.
- The target groups of the questionnaire are private homeowners and tenants. Homeowners are asked to report their financial damage to building structure and building content. Tenants are asked to report on the building content damage of their household and, in case they have detailed information (i.e. bills), on the damage to the structure of the building they live in.
- In cases where tenants or homeowners can only report on one of the damage types, the other one is considered as missing observation. In cases where water entered the building, but did not cause damage to the building content and/or building structure, the respective damage is considered to be zero.
- The questionnaire considers a large set of contextual variables that can potentially explain damage; this list of variables should be based on scientific literature and expert judgments.
- Definitions and variables used in the questionnaire will, as far as possible, be in line with definitions and variables used in other, related questionnaires (i.e. Kreibich et al., 2005; Thieken et al., 2005, 2007; Van Ootegem et al., 2015).
- Closed questions should be incorporated in the design as much as possible to reduce data post-processing efforts, to allow quantitative statistical analyses of the data and to allow comparison within and between data sets (Sarantakos, 2004).
- The questionnaire should be applicable to computer-aided telephone interviewing (CATI) and online surveying; to avoid a “fatigue effect”, the questionnaire should not take longer than 15–20 min to finish (Rathod and LaBruna, 2005);
- The questionnaire should be made generic, so it can easily be adapted to regional specifications when applied internationally.

Item generation

We have built upon a questionnaire developed by GFZ Potsdam and Deutsche Rück, which was originally developed to assess flood damage in the aftermath of the severe flood event that hit Germany in 2002 (Kreibich et al., 2005; Thieken et al., 2005). This questionnaire has undergone several updates since that time. It has been mainly applied to fluvial flooding, i.e. the 2002, 2005, 2006, 2010, 2011 and 2013 floods in Germany (see e.g. Thieken et al., 2007;

Kienzler et al., 2015). It has also been used to investigate pluvial flood events in Lohmar and Hersbruck in 2005 and Osnabrück in 2010 (Rözer et al., 2016). The 2010 survey in Osnabrück was part of a larger survey focusing on fluvial floods and only minor changes were made to the questionnaire. The 2005 survey in Lohmar and Hersbruck, initiated by Deutsche Rück, had a specific focus on pluvial floods, and some of the original questions were tailored to this type of event without completely updating the questionnaire.

The present study is a continuation of the existing line of research. We considerably adjusted the original questionnaire in terms of question items and structure to account specifically for rainfall-related damages to residential buildings. The most important changes are the following:

- We have optimized the questionnaire from around 106 items to 82 items to increase the chance that people will complete the survey. We removed questions that were not or less relevant for extreme rainfall in cities (e.g. whether people received information about river water levels or locations of dike bursts, which river was overflowing, or whether boulders were eroded or deposited because of high flow velocities).
- We added specific questions related to local rainfall conditions (e.g. on the causes of roof leakages, on the available drainage facilities for rainwater and whether wind contributed to the occurrence of water in the house), based on findings from previous studies identifying damage explanatory factors (e.g. Spekkers et al., 2015);
- In line with the study by Van Ootegem et al. (2015), we included items to specify the amount of damage in different parts of the building (i.e. basement, ground floor), rather than asking for a total damage amount only.
- The questionnaire was translated to English and has been made more generic (i.e. not specific to Germany) to make it applicable internationally.
- The questionnaire was modified in such as way that households with no damage could also complete the questionnaire.

The new questionnaire is organized in six thematic groups. Table 3.6 lists the groups and example questions per group. Closed questions were used as much as possible but where relevant respondents could select the answer items “Other, please specify” and “Do not know or prefer not to say”. Question groups were sequenced in such a way that there was a smooth transition between the topics. Moreover, the groups “Hazard characteristics” and “Building information” were put at the start of the survey as some of the items in these groups are conditional for items in next groups. The questionnaire was programmed in the open source survey software LimeSurvey 2.05 (Schmitz, 2016). Six “urban flooding” experts, inside and outside academia, reviewed a draft version of the questionnaire. The entire LimeSurvey questionnaire structure file (.lls) can be downloaded from the DANS archive (Spekkers, 2016).

3.A.2 SI Survey mode and sampling technique

Amsterdam

In Amsterdam, we applied two survey modes:

1. Computer-aided telephone interviewing (CATI), where trained interviewers contacted households by phone and went through the questionnaire using a computer.
2. An online survey, where households completed a web-based version of the questionnaire.

Table 3.6: Questionnaire: item groups and example question items

Item group	No. of questions	Example question items
Hazard characteristics	12	On which date did water get into your house? How did water get into your house? What was the cause of the roof leakage? Which floors of your house were affected by water? Could you give an estimate of the water depth in centimeters in the basement and on the ground floor? How long did the water remain in your house? Was the water contaminated or dirty?
Building information	17	Which of the following building types best describes your house? Do you have a garden adjacent to your house? Which floors does your house have? What is the main flooring material being used for the following floors? Is the roof flat or pitched?
Damage information	14	Did you have damage to your building structure and your building content, or both? Have there been any deformations or collapses of walls or ceilings? What is the total amount of building structure damage in euros? Which building contents were lost or had to be replaced after the rain event? Could you still live in your house?
Preparedness	21	Were you or someone else at home at the time of the rain event? Were you aware of the rainstorm just before it occurred? Which emergency measures were taken as an immediate reaction to the rain event? How many times have you experienced rainwater intrusion in your life before? Have you taken any actions to store rainwater in your garden or improve the infiltration capacity of your garden?
Damage compensation	8	Have your received any form of financial compensation from a third party? What was the size of the insurance claim in Euros? How much compensation have you received by your insurer so far?
Socio-economic variables	10	Do you or someone else in your household renting or owning the house? How many persons are permanently living in your household? What is the net household income per year? What is the highest education you have achieved?
Total no. of questions	82	

We initially considered different survey modes, but we favored CATI for the following reasons: (1) it is consistent with the Münster survey where a CATI campaign was planned; (2) because extreme rainfall impacts is a complex topic, and a CATI approach allows for questions to be clarified where needed; (3) by phone, people could be motivated to participate in the survey even if people thought their damage was not relevant for the research. However, because of the high costs involved in carrying out a CATI campaign (i.e. mainly the costs of hiring staff) and the limited number of phone numbers that could be obtained for the case study area, we eventually select for a mixed-mode survey by combing CATI with an online survey. The online survey does not have the advantage of being able to clarify questions, which may affect the reliability of responses.

The organization of the telephone survey included the sampling of potential survey participants, the training of a team of interviewers, setting up a call center and call center software and writing, mail merging and sending out survey announcement letters.

The sampling was done as follows. We listed the residential addresses located in the case study using the National Building Register (Kadaster, 2013). We only listed addresses located at ground or top floor level, because these floors are most likely to be affected by rainfall. Floor level data are not readily available in the National Building Register. We therefore created an algorithm based on house numbering logic to determine the floor per address. Per address, the phone number of the main tenant or the homeowner was then retrieved through the data enrichment service of the EDM company (`www.edm.nl`). EDM was able to enrich around 30% of the records with one or two phone numbers, including cell-phone numbers. According to EDM, this sample covers all groups of people in the demographic sample. Phone numbers registered in the National Do Not Call Register for consumer research (i.e. MOA research filter, `www.moaweb.nl`) were not used in this study. The sample included 44% landline and 56% cell-phone numbers.

The interviews were carried out by a team of eight MSc students of the TU Delft (four males and four females), with most of them having a background in hydrology and hydraulics. A half-day session was organized to provide the students with project background and instructions. A handbook with tips and fall-back statements (i.e. standard replies to frequently asked questions by the respondents) was provided to the students. The first author was closely involved in the first weeks of the data collection phase to support the interviewers. A dedicated room with computers, phones and headsets was made available by the Product Evaluation Laboratory (PEL) at the TU Delft. The call center was available from 15:00 to 21:00 UTC on weekdays in the period of 20 January to 28 April 2016. We wrote a simple web interface to manage phone calls and appointments using the R shiny package (Chang et al., 2015). Up to five calls were allowed to obtain a completed questionnaire.

A letter was sent to the households to announce the survey the weeks before they were called. A cover letter can increase people's motivation to participate in a survey. In the letter, we introduced the TU Delft, we explained the research background, the scientific and social relevance, why we selected the participant and the Dutch privacy protection regulations the research was bounded to. We also indicated that the survey would take approximately 20 min to finish. People had the opportunity to opt-out if they did not feel like being called. The letters were sent in six batches during the study period to ensure there was not too much time between the letter and the call attempt. More general announcements were done through social media and local websites. The city authorities of Amsterdam were informed prior to the survey.

Households for which no phone number could be retrieved through the EDM data enrichment service were sent a survey invitation letter for the online survey by regular mail. The letter contained a URL to the survey website and a unique token to open the web-based questionnaire. Compared to the telephone survey, some items were removed in the online survey to make the survey 5 min shorter and, thus, more likely to be completed online. Moreover, some items had been slightly rephrased, in their expression only, for online readability.

Two new variables, i.e. “building construction year” and “floor area”, were added to each record based on the National Building Register (Kadaster, 2013).

Münster

In Münster, the survey mode was CATI. Interviews were administered in the period 20 October – 26 November 2015 (i.e. a total of 37 days) by *explorare*, an independent market research institute. They have over 10 years of experience with household surveys on the topic of flood damage (e.g. Kreibich et al., 2005; Thieken et al., 2007, 2016). The main reason for a CATI approach was to have a data set that was consistent with existing CATI data sets.

Samples were drawn by *explorare* from the Deutsche Post address database (6457 phone numbers in Münster and 988 in Greven) for the entire case study area. Due to German privacy protection regulations, this database only contains landline phone numbers of households that did not opt-out of being called for surveys.

A raw text file with the question items and relevance equations was provided to *explorare*, which then coded the questionnaire in VOXCO CATI, a commercial software for professional call centers. Prior to the actual survey, a demo version of the questionnaire was made available for verification purposes. Interviewers were professionals trained by *explorare*. Depending on the available call center capacity, 2 - 10 interviewers were working at the same time. The interviewers received a 1 h introduction to the topic and the questionnaire by the second author of the present paper. There was a feedback round after the first five completed surveys.

The survey was announced via a press release, which was picked up by at least six local and regional newspapers as well as local radio stations. Additionally, the survey was announced through the city websites. The city authorities of Münster and Greven were informed prior to the survey. They distributed the information via online and offline public notice boards.

Data availability: The databases of survey responses of the Amsterdam case are available under Creative Commons Attribution-NonCommercial license (CC BY-NC) and can be downloaded from the DANS archive (Spekkers, 2016). The questionnaire used in Amsterdam can be downloaded from the same source. The survey responses of the Münster case will be available through the HOWAS21 database (GeoForschungsZentrum GFZ, 2017) five years after the end of the EVUS project (BMBF, 03G0846B), i.e. June 2023.

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4 Probabilistic models significantly reduce uncertainty in Hurricane Harvey pluvial flood loss estimates

Summary. Pluvial flood risk is mostly excluded in urban flood risk assessment. However, the risk of pluvial flooding is a growing challenge with a projected increase of extreme rainstorms compounding with an ongoing global urbanization. Considered as a flood type with minimal impacts when rainfall rates exceed the capacity of urban drainage systems, the aftermath of rainfall-triggered flooding during Hurricane Harvey and other events show the urgent need to assess the risk of pluvial flooding. Due to the local extent and small-scale variations, the quantification of pluvial flood risk requires risk assessments on high spatial resolutions. While flood hazard and exposure information is becoming increasingly accurate, the estimation of losses is still a poorly understood component of pluvial flood risk quantification. We use a new probabilistic multivariable modeling approach to estimate pluvial flood losses of individual buildings, explicitly accounting for the associated uncertainties. Except for the water depth as the common most important predictor, we identified the drivers for having loss or not and for the degree of loss to be different. Applying this approach to estimate and validate building structure losses during Hurricane Harvey using a property level data set, we find that the reliability and dispersion of predictive loss distributions vary widely depending on the model and aggregation level of property level loss estimates. Our results show that the use of multivariable zero-inflated beta models reduce the 90% prediction intervals for Hurricane Harvey building structure loss estimates on average by 78% (totalling U.S.$3.8 billion) compared to commonly used models.

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4.1 Introduction

Quantifying the future economic risk of pluvial flooding is critical for climate change adaptation of an increasing urban population. Pluvial, or often referred to as surface water flooding, is directly caused by extreme rainstorms with rainfall rates exceeding the capacity of the urban drainage system. Cities around the globe have been impacted by recent pluvial flood events. Large-scale pluvial flooding in the Houston area in Texas during Hurricane Harvey has led to 68 deaths and estimated total damage in the range of U.S.$90 to 160 billion, making it the second most expensive natural disaster in the history of the United States (Blake and Zelinsky, 2018). Other examples include flooding after a rainstorm in Copenhagen 2011 causing total economic damage of U.S.$ 1 billion (Wojcik et al., 2013) or in Beijing 2012 causing total economic damage of U.S.$ 1.86 billion and 79 fatalities (Wang et al., 2013).

An increasing pluvial flood risk caused by an expected increase of intensity and frequency of heavy precipitation events (Donat et al., 2016; Kundzewicz et al., 2014) combined with an ongoing urbanization with a concentration of population and assets in cities (Kaspersen et al., 2015) motivates the need to assess the current and future risk of pluvial flooding. A review by Rosenzweig et al. (2018) identified the lack of knowledge in the quantification of present and future pluvial flood impacts as one of three key research areas for the development of flood resilient cities. However, pluvial flood risk is mostly excluded or neglected in flood risk analysis, although there is evidence that the high frequency of these events lead to long-term cumulative losses comparable to less frequent but severe flood events (Ten Veldhuis, 2011). This lack of knowledge includes risk management and mitigation plans. With few exceptions, official flood hazard maps are exclusively focused on fluvial and coastal flood risk. For the conterminous United States, Wing et al. (2018) found that the poor coverage of urban catchments in flood hazard maps produced by the Federal Emergency Management Agency (FEMA), has lead to an underestimation of the population affected by pluvial and fluvial flooding by a factor of 2.6 - 3.1.

With scarce information on the hazard, only few loss estimation models for pluvial floods have been developed. Existing approaches include adapting water depth - damage functions (also known as stage-damage models) from river floods (Freni et al., 2010; Zhou et al., 2012; Olsen et al., 2015), using multiple linear regression models (Van Ootegem et al., 2015) or by correlating rainfall measurements with insurance claims or survey data (Spekkers et al., 2014; Van Ootegem et al., 2018). However, the lack of data, the complex nature of the hazard and impact as well as the lack of a consistent quantification of the associated uncertainties, has so far hampered an extensive estimation of expected pluvial flood losses needed to decide on adaptation strategies in cities. Van Ootegem et al. (2015, 2018) construct different multivariate pluvial flood damage models from survey data of a study in Belgium based on water depth-damage and rainfall-damage relationships. Key findings of their study include the importance of additional non-hazard variables such as risk awareness and the effect of reported zero loss cases. However, the results do not provide information as to whether additional variables can also improve loss estimates.

In this study, we use probabilistic high-resolution loss models to estimate pluvial flood losses on different spatial scales. Unlike widely used deterministic stage-damage functions, these probabilistic univariable and multivariable loss models provide a consistent approach to quantify how certain a loss prediction is by providing predictive distributions instead of point estimates. Application and validation of different high-resolution probabilistic loss models in Harris County, Texas, reveal significant differences in the dispersion and reliability of property and county level pluvial flood loss predictions for Hurricane Harvey. Only two out of the six tested models reliably predicted the reported loss with a difference of 78% in the 90%

prediction intervals between the two models equaling to an absolute difference of U.S.$3.8 billion for pluvial flood building structure loss in Harris County. These results have major implications for cost-benefit analysis of flood risk management and adaptation decisions in cities.

4.2 Background

With the need to adapt cities to an expected increase in pluvial flood risk, decision makers face the challenge to take appropriate decisions under the uncertainty of how the risk of pluvial flooding evolves in the future including the expected losses. As uncertainties in flood losses estimates are usually high, probabilistic loss models could greatly aid a comprehensive pluvial flood risk management (Todini, 2018). Unlike deterministic estimates, probabilistic predictions provide continuous predictive distributions where the dispersion of the distribution can provide the range an expected loss would fall in with a certain probability (e.g., 90%). The reliability of a probabilistic prediction can be expressed as the ability of the predictive distribution to cover the actual observed loss.

Although probabilistic loss models have been developed for river floods (Dottori et al., 2016; Kreibich et al., 2017; Schröter et al., 2014), these models are the exception and deterministic estimates based on empirical or synthetic relationships between the water depth and the absolute or relative building loss are still widely used for loss estimations for all types of flooding (Gerl et al., 2016; Merz et al., 2010; Scawthorn et al., 2006). The resulting loss estimates in these stage-damage functions are commonly expressed as point estimates for the repair and/or replacement costs in monetary values (i.e., U.S.$) or percentage of the depreciated value of a building. Instead of a direct quantification of uncertainty inherent to probabilistic predictions, uncertainty in stage-damage functions is often based on expert judgment and/or by calculating a range of possible outcomes using different loss functions (Dittes et al., 2018). Missing information, and/or a lack of consistency in quantifying how certain a loss estimate is, makes it challenging for decision makers to, for example, evaluate the potential of an adaptation measure to reduce future losses.

While the deviations of point estimates for deterministic loss models are often shown to be reasonably small for loss estimates on large spatial scales typical for river or coastal flooding, loss predictions become highly uncertain on smaller scales (i.e., individual buildings)(Merz et al., 2004; Scawthorn et al., 2006). However, due to the local extent and small-scale variations, reliable small-scale loss models are required to quantify pluvial flood risk for a specific location.

In this context, we use machine learning as well as different univariable and multivariable probabilistic approaches to investigate three main research objectives: we (i) identify important loss influencing variables and their effect on the uncertainty of loss predictions; (ii) analyze the potential of parametric and nonparametric probabilistic approaches on reducing the dispersion and increasing the reliability of building-level loss estimates; and (iii) evaluate the applicability of probabilistic multivariable loss models in the context of new sensors and data sources for pluvial flood loss estimation on different spatial scales (Ford et al., 2016; Schröter et al., 2018).

4.3 Materials and methods

4.3.1 Data

We construct a data set that consists of self-reported pluvial flood losses and related information of private households. The data were obtained through a standardized questionnaire using computer-aided telephone surveys after pluvial flood events in five cities in Germany between 2005 and 2014 (Rözer et al., 2016; Spekkers et al., 2017). Based on 120 items in the questionnaire, a data set with 56 predictors and two loss variables is constructed covering eight groups: reported loss, hazard, warning, emergency response, precaution, experience, building information, and social-economic information. The loss variables are represented as relative loss (*rloss*) and a variable with binary information if a building suffered from structural damage or not (*dam*). *rloss* is on the scale from 0 (no loss) to 1 (total loss), normalizing the reported direct building loss in Euro [EUR] with the total replacement cost value less depreciation of the respective building. We exclude observations where *rloss* could not be derived due to missing information on the building replacement value or the reported loss itself resulting in a total of 431 observations.

Out of 56 predictors in the data set, 12 are excluded from the analysis, because of their zero or near-zero variance, resulting in 44 variables to be considered for further analysis. To address the issue of censoring zero loss observations, pluvial flood affected households without direct building loss are included in the data set if water intrusion into the building was reported (9% of observations) (Van Ootegem et al., 2015). Missing values in other variables were imputed using complementary information available in the questionnaire (i.e., missing information of the total living area through building footprint and number of habitable floors). In few cases where causal inference was not possible, missing values are imputed using nearest neighbor imputation. A more detailed description of the data including a table describing all 56 predictors, the two loss variables, the variables excluded from the analysis, and the percentage of imputed missing values is provided in the supporting information (SI) in Section 4.A.1 - *Survey data*.

4.3.2 Detection of important loss-influencing variables

Prior to the actual model development, we screen the previously described data set for variables with the highest predictive power given the complex correlations and interdependencies in the data set using machine learning. A reduced set of variables out of the full 44 variables is then used to develop the multivariable probabilistic models described in the following section. The most important loss influencing variables are detected by using an ensemble of variable importance measures of two tree-based (Bagging (cRF); (Strobl et al., 2007) and Boosting (GBM); (Friedman, 2001)) and two linear regression-based (Ridge; (Hoerl and Kennard, 1970) and LASSO; (Tibshirani, 1996)) machine learning algorithms.

The four different types of algorithms are used in two different settings: a binary classification between *loss/no loss (dam)* and a regression analysis modeling the *degree of loss (rloss)* of a building. Based on the variable importance score of each variable, its rank within each ensemble member as well as its overall rank is determined. The top five variables with the highest overall rank for *rloss* and *dam* are further considered in the model development process. For details on the variable selection procedure, see SI in Section 4.A.2 - *Determining important predictors.*

4.3.3 Probabilistic loss estimation models

Bayesian zero-inflated beta regression (Ospina and Ferrari, 2010) is used to predict the relative loss to a building by pluvial flooding (*rloss*) using the previously selected important loss influencing variables. The probabilistic prediction y for *rloss* on the interval [0,1) is modeled as follows: We define z_i to be a binary variable for the occurrence of flooding in the ith observation and estimate it with a logistic regression:

$$z_i \sim Bernoulli(\gamma X_i) \tag{4.1}$$

where X_i is the vector of predictors for the ith observation, γ is the vector of coefficients, and Bernoulli(Θ) indicates a Bernoulli trial with probability Θ. Once z_i is known, then we can calculate y_i following a zero-inflated Beta regression model

$$y_i = \begin{cases} Beta(\alpha_i, \beta_i) & z_i = 1 \\ 0 & z_i = 0 \end{cases} \tag{4.2}$$

where $\alpha_i > 0$ and $\beta_i > 0$ are the shape and scale parameters, respectively, of the Beta distribution. To estimate these parameters, we define

$$\alpha_i = \mu_i \phi \tag{4.3}$$

$$\beta_i = (1 - \mu_i)\phi \tag{4.4}$$

following (Ferrari and Cribari-Neto, 2004)

$$\mu_i = X_i \beta \tag{4.5}$$

where β is the coefficient vector for the Beta regression. In summation, our zero-inflated Beta regression model conducts simultaneous inference on the vector γ, the vector β, and the scalar ϕ, given observations of flood occurrence z, flood damage y (i.e., the variable *rloss*), and predictive variables X.

The probabilistic predictions of *rloss* from the Bayesian zero-inflated Beta model (*Beta*) are compared with probabilistic predictions of two additional model types used for empirical flood loss estimation in previous studies. A simple Bayesian parametric model based on a *Gaussian* response distribution is used as a probabilistic representation of a model type widely used in flood loss estimation (Gerl et al., 2016; Van Ootegem et al., 2015) and a nonparametric model based on the *RandomForest* algorithm, used for probabilistic flood loss estimation in previous studies (Schröter et al., 2016). The three model types (*Beta, Gaussian,* and *RandomForest*) are fit as univariable and multivariable models (i.e., with a single predictor in X or with multiple predictors) to investigate the effect of additional variables on the predictive performance, resulting in six different models in total. The univariable models are fit using water depth *wd* as their only predictor, reflecting the current standard in flood loss estimation (Gerl et al., 2016; Merz et al., 2010). The univariable parametric models (*Beta* and *Gaussian*) are fit with the square root of the water depth to be comparable with reference functions in previous studies (Merz et al., 2013; Schröter et al., 2014; Wagenaar et al., 2017). All multivariable models use the set of predictors shown in Table 4.1. For more details on the models including details on the priors of the Bayesian models, see SI 4.A.2 - *Probabilistic multi-variate beta model.*

4.3.4 Model validation and comparison

We validate the probabilistic loss predictions on the building level for the previously described models and data using 10-fold cross validation. For determining the error of the point estimate (median of the predictive distribution), the root-mean-square error (RMSE) and the mean bias error (MBE) are used. For validating and comparing the reliability of the loss estimate, we calculate the hit rate (HR), meaning the percentage of cases where the observed value lies within the 90% highest density interval (HDI) of the predictive distribution. We use the width of the 90% HDI to evaluate the dispersion of the predictive distribution. In addition, we calculate the interval score, a combined dispersion and reliability score, penalizing predictions based on the width of the 90% HDI and the percentage of observations that are outside the 90% HDI of the respective predictive distributions (Gneiting and Raftery, 2007).

To evaluate the effect of including the option to have no building loss in the model, we validate and compare the different models for three scenarios: one where zero-loss observations are removed from the data set prior to fitting the model, one where the zero-loss observations are kept in the data set (zero-loss proportion 9%), and one where the proportion of zero-loss observations is upsampled to 20%. Details on the validation procedure and the different scores used to compare the models are provided in SI 4.A.2 - *Model comparison and scoring methods*.

4.3.5 Application Harris County, TX

We apply the previously trained probabilistic loss models in Harris County, TX, to analyze the potential for reducing the dispersion and improving the reliability of probabilistic loss estimates for direct building damage of private households caused by pluvial flooding during Hurricane Harvey. To demonstrate the feasibility of probabilistic building-level loss estimation, we construct a high-resolution data set from publicly available data sources for Harris County, TX.

Based on refined pluvial flood inundation maps for Hurricane Harvey provided by *JBA Risk Management* (JBA Risk Management, 2017), detailed information of affected properties are gathered from the *Harris County Appraisal District Real & Personal Property Database* including the type and value of each affected building (HCAD, 2018). In addition, census information is used to derive the average household size on the block level (U.S. Census Bureau, 2016). Besides this information, the constructed data set contains data on the knowledge about the flood hazard based on if a property is within the 100-year flood zone derived by FEMA (Zone A) and the probability of a property being affected by contamination. The contamination data was created by spatially interpolating reported point sources of contamination from the *National Response Center of United States Coast Guard* and volunteered geographic information using 2-D kernel density interpolation (NRC, 2018; Sierra Club, 2017). The resulting dataset for Harris County contains information of more than 304 000 individual buildings affected by pluvial flooding during Hurricane Harvey.

For validation and visualization the property level loss distributions of each model are aggregated on the zip code as well as on the county level. The aggregated loss estimates are validated using the sum and average total building damage from FEMA's Housing Assistance Program available on the zip code level as well as for the entire county for Hurricane Harvey (FEMA, 2018*a*). Details on the data sets and models used in Harris County including the validation data are provided in SI 4.A.1 - *Harris County data*.

4.4 Results

4.4.1 Important loss influencing variables

Screening the high-dimensional data set for the most important loss influencing variables to be considered in the probabilistic loss models, we find that the drivers for having loss or not having any loss (*dam*) and the drivers for the degree of loss (*rloss*) to a building are different, indicating different damaging mechanisms. While both cases share the water depth as the most important predictor, other important predictors hardly overlap. Looking at the second to fifth most important predictors for *dam*, the resistance of a building and its inhabitants is decisive. Given a low inundation depth, larger households, multifamily buildings, younger residents, and residents who previously informed themselves about pluvial flooding have a lower probability of having any loss. In contrast, the second and fourth most important predictors influencing *rloss* are directly related to the flood intensity. Higher inundation depths, longer flood duration, and contamination of the flood water lead to higher losses. The variable importance scores of

Table 4.1: Mean variable importance scores of the five most important predictors for rloss and dam on the scale (0, 100) for each ensemble member (Tree-Based Bagging [cRF] and Boosting [GBM]; Penalized Regression with L1 [LASSO] and L2 [Ridge] Regularization). Corr indicates direction of the trend: '+' increasing, '-' decreasing. Superscript numbers indicate rank within each ensemble member. Avg. rank indicates the overall rank based on the median rank of each ensemble member

Name	**Variable**	**cRF**	**GBM**	**LASSO**	**Ridge**	**Avg. rank**	**Corr**
			Degree of loss				
Water depth	wd	100^{1}	100^{1}	94^{1}	97^{1}	1	+
Duration	d	38^{2}	50^{2}	81^{3}	90^{2}	2	+
Basement [Y/N]$^{+}$	bu	12^{9}	11^{13}	84^{2}	85^{3}	6	+
Contamination [Y/N]	con	15^{8}	9^{17}	77^{4}	81^{4}	6	+
Household size^{+}	hs	17^{4}	17^{8}	45^{7}	64^{5}	6	−
			Loss/no loss				
Water depth	wd	99^{1}	100^{1}	89^{1}	90^{2}	1	+
Household size	hs	84^{2}	14^{2}	67^{3}	93^{1}	2	−
Knowledge hazard	pre1	72^{3}	6^{4}	48^{7}	81^{3}	3.5	−
Age of respondent^{+}	age	69^{4}	13^{3}	3^{32*}	42^{9}	6.5	+
Multi-family home[Y/N]	bt	49^{7}	1^{11*}	50^{6}	51^{6}	6.5	−

* Importance scores not stable
\+ showed no improvement in the predictive performance of the probabilistic loss models and were therefore not considered in the final models

the five most important predictors of the four machine learning algorithms, their rank within each ensemble member and the median rank of all ensemble members are summarized in Table 4.1. Starting with the most important predictor both the overall rank and the importance scores drop sharply. Of the five preselected important loss influencing variables shown in Table 4.1, we find three variables for *rloss* and four variables for *dam* to improve the predictive performance in the probabilistic loss models. Variable importance values for all 44 variables and differences between the machine learning algorithms are shown in SI 4.A.3 *Results.*

4.4.2 Predictive performance of probabilistic models

The prediction performance of the six probabilistic models (univariable and multivariable models for *Gaussian, RandomForest,* and *Beta*) for the cross-validated predictions are summarized in Table 4.2. Looking solely on the error of the point estimate of the predictions (median of the predictive distribution), we find only a minor nonsignificant reduction in root-mean-square error for the three models for both the univariable and multivariable versions. However, for the 90% HDI of each predictive distribution, the parametric *Beta* and *Gaussian* models are significantly more reliable with an average HR of 97% and 95% for the univariable and multivariable *Beta* models and 91% for both *Gaussian* models compared to 67% and 49% for the *RandomForest* counterparts. However, when we control the HR of the predictive distributions for dispersion and distance to missed observations using the interval score, the high HR scores of the *Gaussian* models can be attributed to consistently wider 90% HDI's (see Figure 4.1B) compared to the other two models. The difference in shape and width of the predictive distributions of the different models is illustrated in Figure 4.1A, for the example of a loss estimate for a single building with an observed *rloss* of 0.016. While the *RandomForest* models tend to give very sharp predictive distributions with shapes close to a normal distribution, the predictive distributions of the *Gaussian* and *Beta* models both have longer tails. The almost lognormal

Table 4.2: Performance of loss model predictions for out of sample observations (median). Standard deviation in brackets. RMSE = root-mean-square error; MBE = mean bias error

Model type	**Variables**	**RMSE**	**MBE**	**Hitrate[1]**	**Interval Score[1]**
Gaussian	uni-variate	.028 (.018)	.015 (.008)	.91 (.01)	.26 (.01)
	multi-variate	.027 (.017)	.013 (.007)	.91 (.02)	.25 (.02)
RandomForest	uni-variate	.028 (.017)	0* (.009)	.49+* (.07)	.17* (.11)
	multi-variate	.025 (.016)	.005 (.008)	.67+* (.08)	.11* (.08)
Beta	uni-variate	.027 (.017)	.010 (.008)	.97 (.06)	.09* (.08)
	multi-variate	.025 (.017)	.009 (.008)	.95 (.07)	.08* (.08)

[1] 90% highest density interval (HDI)
* Significantly different from Gaussian model for the .05 significance level(uni- and multivariate models respectively)
+ Significantly different from univariate models for the .05 significance level for each model type

shape of the *Gaussian models* is caused by the backtransformation of the logit-transformed predictive distribution. Although the sharp predictive distributions of the *RandomForest* models lead to considerably narrower prediction intervals it significantly increases the risk of the 90% HDI not covering the actual observed loss (see Table 4.2). With its flexibility in shape and clearly defined interval of the response distribution, we find the *Beta* models to provide the best trade-off between reliability and dispersion. Compared to the widely used reference function (univariable *Gaussian*), the univariable and multivariable models have between 47% and 50% narrower HDI's with HRs above 90%. Comparing the difference between the univariable and multivariable models, we find an increase in the variability in shape and width of the predictive distributions for all multivariable models. Although this increase in variability only show a minor, nonsignificant improvement in accuracy, reliability, and dispersion (see Table 4.2), we find that multivariable models perform significantly better compared to models using the water depth as only predictor when individual predictions are aggregated (see Figure 4.3C).

4.4.3 Effect of zero-loss cases on the damage estimates

The often low water levels of pluvial flooding compared to river or coastal flooding increases the chances that direct building loss can be completely avoided, although water entered the building. Analyzing different zero-loss proportions, we find that not explicitly accounting for these cases can considerably affect model predictions in terms of reliability and dispersion of the predictive distribution.

For the *Gaussian* models, none, and for the multivariable *RandomForest* model, 28 of the 38 zero-loss observations in the data set were inside the respective 90% HDI. For increasing the zero-loss proportions we observe a significant increase in the reliability of the *RandomForest* model and a significant increase in the width of the 90% HDI of the loss prediction for the *Gaussian* model (Figure 4.2). The increase in reliability of the *RandomForest* model reflects the capability of the model to learn implicitly to account for zero-loss cases, when the learning sample becomes large enough. Without the possibility to consider zero-loss cases, a higher proportion of zero-loss observation simply adds additional variability, which the *Gaussian* models cannot explain. Bias caused by varying zero-loss proportions is found to be reduced to a minimum by explicitly accounting for zero-loss observation in the (zero-inflated) *Beta* models (see *Beta* model in Figure 4.2). Findings for the univariable models are, for the sake of readability, shown in SI 4.A.3 *Results*.

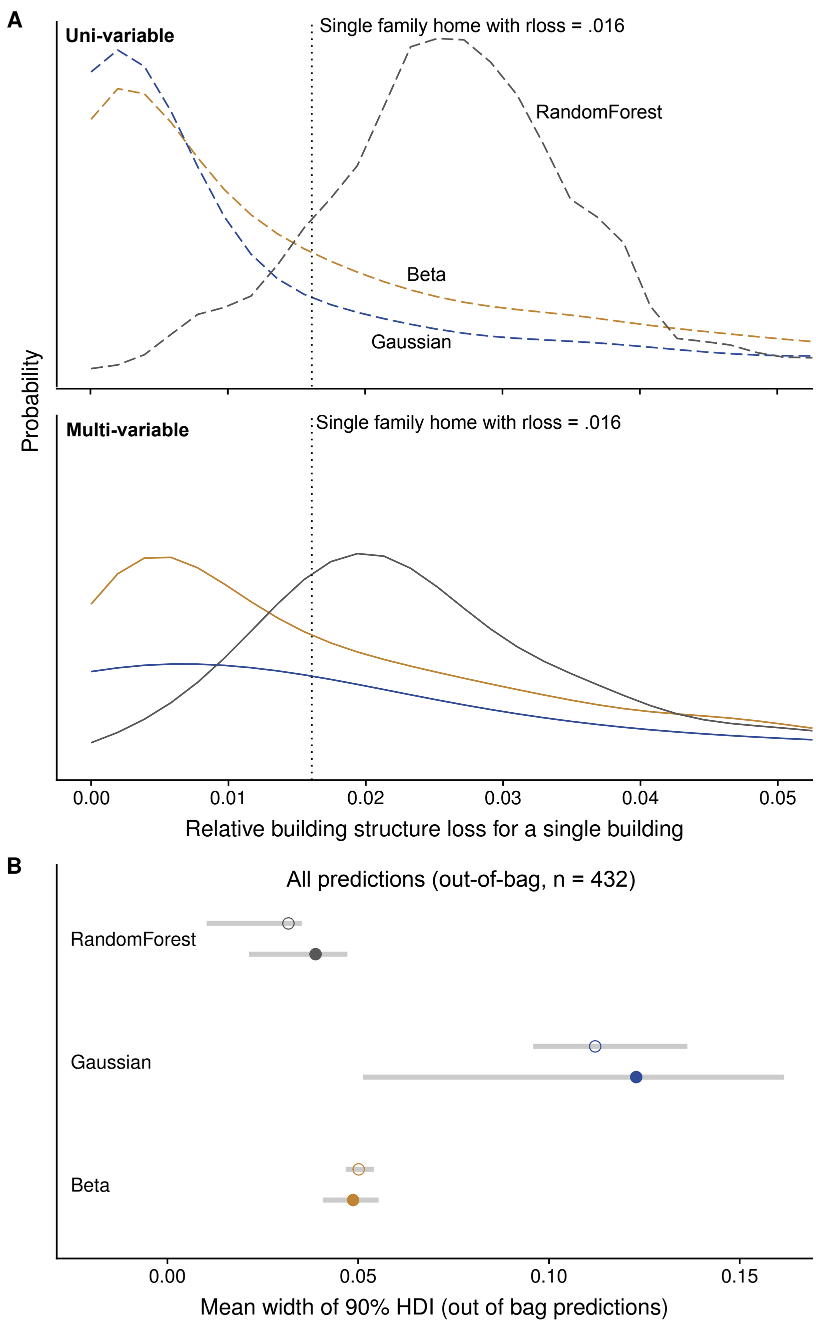

Figure 4.1: Probabilistic predictive distributions of different uni- and multi-variable models (*RandomForest, Gaussian, Beta*) for cross-validated observations. The predictive distributions for *Gaussian* and *Beta* models are based on 2000 MCMC samples from the respective posterior predictive distributions. The predictive distributions from *RandomForest* model are based on the predictions of 2000 individual trees used for training the forest. (A) The different predictive distributions for a single household (single family home) with a recorded relative loss of .016 (dotted vertical line). The upper plot of (A) shows the predictive distributions for three uni-variable models using the water level as only predictor (dashed lines). The lower plot of (A) shows the same three model types, but with 5 additional predictors (solid lines). In (B) the widths of the 90% HDI for the predictive distributions of all cross-validated observations (n=432) is summarized. The points show the medians for the uni-variable (hollow) and multi-variable (solid) models for the three different model types.The grey boxes show the 25th to 75th percentile ranges for each model. HDI = highest density interval.

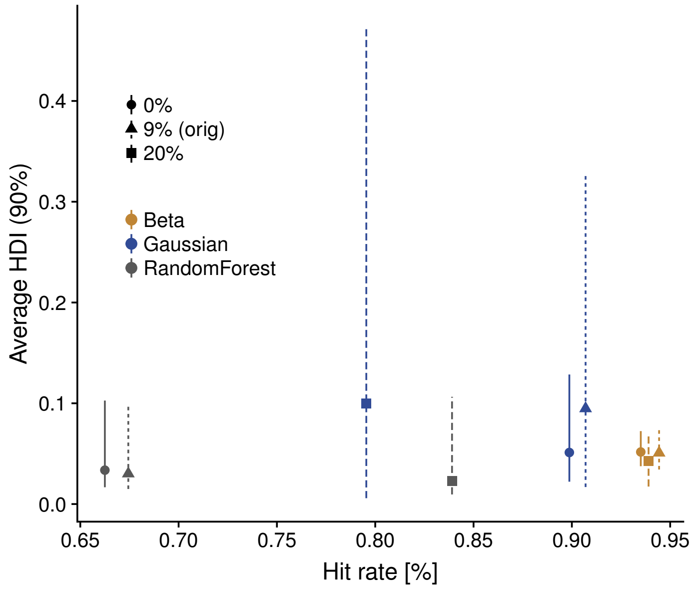

Figure 4.2: Trade-off between reduction in uncertainty and reliability for cross-validated predictions for different multivariable loss models and different proportions of zero-loss observations in the data set. Results for univariable models are shown in SI (Results section). Uncertainty is represented as mean width of the 90% HDI for all observations. Reliability is represented as proportion of the out-of-sample observation, which are inside the respective 90% HDI. Error bars represent the 90% interval for the HDI width of all out-of-bag predictions. HDI = highest density interval.

4.4.4 Hurricane Harvey building loss for Harris County, TX

Modeled direct losses to the building structure caused by pluvial flooding during Hurricane Harvey in Harris County, TX, are summarized in Figure 4.3. Our main finding is that the width of the 90% HDI of the predictive distribution for individual buildings can be reduced by 21% or U.S.$3,685 on average when using the multivariable *Beta* model instead of the univariable *Gaussian* model representing the current standard in empirical flood loss estimation. Panel B shows the mean relative reduction in the width of the 90% HDI between the two models for individual buildings on the zip code level. For individual buildings we find spatial variations for the average building structure loss ranging from U.S.$544 to U.S.$10,134 with the majority of areas being in the range of U.S.$2,000 to U.S.$5,000. The highest average building structure loss with values above U.S.$7,500 are found west and southwest of Downtown Houston (Panel A).

For the aggregated predictive distribution of the absolute loss to the building structure of over 304 000 affected residential buildings (single-family and multifamily homes) in Harris County, the corresponding samples of the individual predictive distributions of each building are summed up. This leads to an effect, known as the central limit theorem, where the Beta-distributed predictive distributions for individual buildings coming from the *Beta* model tend to form a normal distribution when enough individual predictive distributions are summed. In combination with a higher variability, introduced by the additional variables, the considerably higher reliability and lower dispersion of the multi-variable *Beta* model compared to the univariable *Gaussian* model on the building-level vanishes when the predictions are aggregated over a large amount of individual buildings (Panel C).

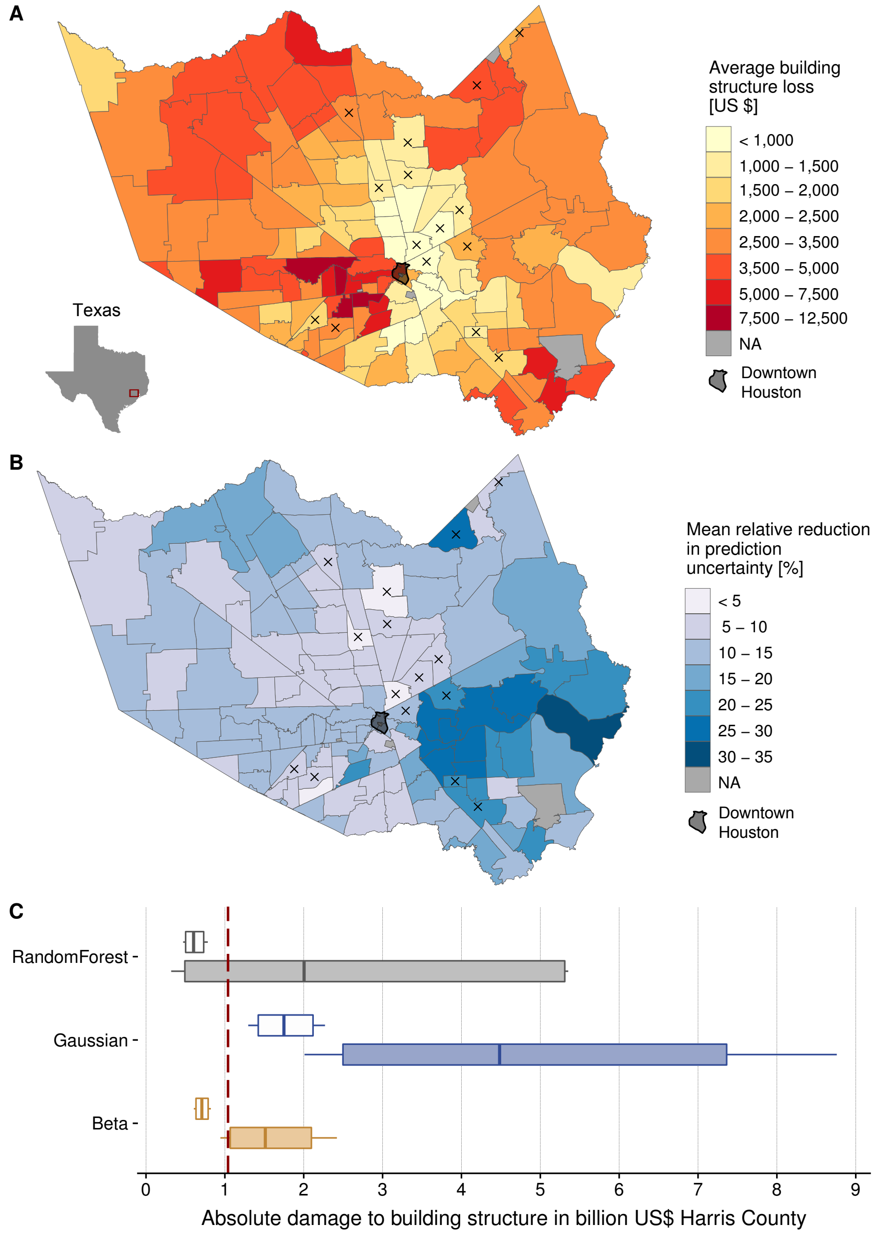

Figure 4.3: Modeled direct building structure losses for Harris County, TX, caused by pluvial flooding during Hurricane Harvey. (A) The modeled average building structure loss per building aggregated on the zip code level using the multivariable *Beta* model. (B) The average relative reduction in uncertainty (expressed through the width of the 90% HDI) per building between the univariable *Gaussian* model (reference function) and the multivariable *Beta* model in percent aggregated on the zip code level. Crosses in (A) and (B) indicate zip code areas where the reported average building loss is outside the 90% HDI of the modeled average building loss. (C) Box plots of the aggregated predictive distributions of the absolute direct building structure damage for the entire county for three different model types (*RandomForest*, *Gaussian* and *Beta*) in their univariable (hollow) and multivariable (solid) versions. Bars indicate the median absolute loss, boxes the 90% HDI, and whiskers the 98% HDI of the absolute direct building loss for Harris County. The red dashed line represents the official reported absolute building structure loss based on data from the Federal Emergency Management Agency Housing Assistance Program. HDI = highest density interval.

This effect is also described by Sieg (2019) and provides further evidence why univariable stage damage functions based on *Gaussian* response distributions yield sufficiently accurate loss predictions on larger scales while the same model produces highly uncertain loss estimates on the building level. For results aggregated to the county level, we find univariable and multivariable *Gaussian* models to overestimate the absolute building structure losses by U.S.$0.7 and U.S.$3.4 billion, respectively. This can be partly attributed to the underestimation of zero-loss cases described in the previous chapter, which leads to higher intercepts in the model. For the multivariable model this effect is considerably stronger as the model is fit as a linear instead of a square root function (see Section 4.3.3). Of the six models tested, none of the univariable models, and only the aggregated predictive distributions of the multivariable *RandomForest* and *Beta* models are covering the reported loss from FEMA's Housing Assistance Program (U.S.$1.04 billion). Here the multivariable *Beta* performs significantly better with a total reduction in width of the 90% HDI of U.S.$3.8 billion (or 78%) compared to the multivariable *RandomForest* model, providing the best trade-off between dispersion and reliability.

4.5 Discussion and Conclusions

Despite causing severe losses in cities around the globe, pluvial flooding is still widely neglected when estimating the current and future flood risk in urban areas. This results in a widespread underestimation of flood risk especially in urban areas where fluvial or coastal floods are not the dominant sources of flooding (Rosenzweig et al., 2018). One key limitation in reliably quantifying pluvial flood risk is the local extend of pluvial floods, requiring loss estimates on spatial scales where damaging processes are still hardly understood and the associated uncertainties are often unknown.

We present the first consistent quantification of uncertainties in pluvial flood loss models for private buildings in the shape of predictive distributions using a fully probabilistic modeling approach. We train and validate different univariable and multivariable probabilistic loss models with a local training data set and use these models for a probabilistic estimate of building structure losses of over 304 000 individual buildings in Harris County during Hurricane Harvey. Our analysis reveal significant differences in the dispersion and reliability of the continuous predictive distributions between different models depending on (i) the use of additional predictors, (ii) the choice of response distribution, (iii) the ability of the model to account for zero-loss cases, and (iv) the spatial scale of the analysis. We find that the assumption of a normal or lognormal distribution of uncertainties in loss estimates, which most loss models implicitly use today, results in unnecessarily wide prediction intervals. In the case of property level predictive distributions, we find that the width of the 90% HDI exceeds the median of the prediction by factor 30 on average. Our results suggest that the with of the 90% HDI for pluvial flood loss estimates on the property level can be significantly reduced by 47% when using a zero-inflated Beta distribution instead of normal response distributions without sacrificing the reliability (Table 4.2).

While not evident on the property level, we find that using water depth as only predictor results in an underestimate of the prediction intervals leading to unreliable loss estimates when spatially aggregating loss predictions (Figure 4.3C). Here, we find additional predictors to improve the pluvial flood loss predictions in two ways: (i) by increasing the variability of individual predictive distributions leading to a more realistic representation of uncertainties when aggregating estimates and (ii) by improving the detection of cases where water entered the building but did not cause any monetary damage to the structure (Figure 4.2). For the latter our analysis indicate the ability of households to prevent direct damage to their homes should be included in loss models. The analysis of important loss influencing variables has further shown that the probability of a household to not have any monetary loss to the building structure is — other than for the degree of loss — strongly influenced by household characteristics such as the number of people living in a household and their prior knowledge about the pluvial flood hazard. This highlights the need to account for differences in the ability of households to reduce or avoid damage to their homes in loss models for pluvial floods.

For loss estimates in Harris County, the use of additional predictors in zero-inflated Beta models considerably increases the reliability while at the same time significantly reduces the dispersion of the predictive distribution given validation data. For direct building losses aggregated on the county level this reduction accounts for U.S.$3.8 billion or 78% compared to loss models based on normal response distributions. These findings are relevant for a larger discussion on using probabilistic loss estimates for decision making in flood risk management. This includes the potential of probabilistic approaches to improve the spatial transferability of loss models. We further demonstrate the potential to significantly improve the dispersion and reliability of pluvial flood loss estimates using probabilistic models, which goes beyond previous studies considering only point estimates (Van Ootegem et al., 2015; Zhou et al., 2012). Although these results are limited to a quantification of uncertainties of loss predictions, the results can easily be extended for robust decision making on adaptation strategies based on exceeding probabilities, which can be directly derived from predictive distributions. While our results suggest that models that use a zero-inflated Beta response distribution provide predictive distributions with a significantly lower dispersion and higher reliability, a general paradigmatic change toward probabilistic models would greatly aid a better understanding of uncertainties in loss models (Todini, 2018). Same is true for multivariable models, where emerging cloud-based reporting systems and open data portals now allow the use of high-dimensional data sets in flood loss modeling.

4.A Supporting Information (SI)

4.A.1 SI Data

Survey data

The data set contains information collected by computer aided telephone interviews (CATI) of private households affected by pluvial floods in 2005, 2010 and 2014 in five German cities (Table 4.3). Altogether 783 completed interviews are available from these surveys. On the basis of information from fire brigades or flood reports and press releases, lists of inundated streets were compiled for each flood event. These lists served as a basis to select telephone numbers of all potentially affected households from the public telephone directory. Computer-aided telephone interviews were undertaken by a market research institute with the help of the VOXCO software package (`www.voxco.com`) about 15 to 19 months after the events (Table 4.3). At the beginning of the interview, it was asked to interview the person in the household with the best knowledge about the flood event. The questionnaires used for the surveys were based on a questionnaire developed by Kreibich et al. (2005) and Thieken et al. (2005) for river floods, but was adapted for the special characteristics of pluvial flooding. The interviews lasted 25 to 30 min on average and contained approximately 110 questions on the following topics: flood impact, warning, emergency measures, evacuation, clean-up, characteristics of and damage to household contents and buildings, recovery of the affected household, precautionary measures, flood experience, and socio-economic characteristics of the household.

Building loss includes all costs associated with repairing the damage to the building structure, such as plastering, replacing broken windows and repairing the heating system. The questionnaire contained detailed questions addressing not only total loss but also the affected stories, many information on the building itself necessary to estimate the building value. This generated the most accurate information possible about the flood loss. Post-processing was performed, like correcting or removing implausible inputs, for example, by comparing reported water levels inside and outside the house and by comparing reported floor areas with building footprint. More details on the surveys and dataset are provided by Rözer et al. (2016) and Spekkers et al. (2017).

Table 4.3: Overview survey data

Characteristics	**Surveys**		
Survey period	Nov 2006	Feb/Mar 2012	Oct/Nov 2015
Affected cities	Lohmar Hersbruck	Osnabrück	Münster Greven
Event	Jun 2005	Aug 2010	Jul 2014
Number of households interviewed	173	100	510
References	URBAS (2008), Rözer et al. (2016)	Rözer et al. (2016)	Spekkers et al. (2017)

Relative loss

The relative loss (*rloss*) describes the proportion of the direct monetary damage to the structure of a building in relation to its total value. It is bounded between the interval [0,1], where 0 is equivalent no monetary damage at all and 1 to a total loss of the building. Modeling the proportion of the direct monetary damage instead of the total values has two main advantages when modeling losses: (i) the loss estimates become independent from the actual building values, which is expected to lead to more stable relationships between *rloss* and the predictors;

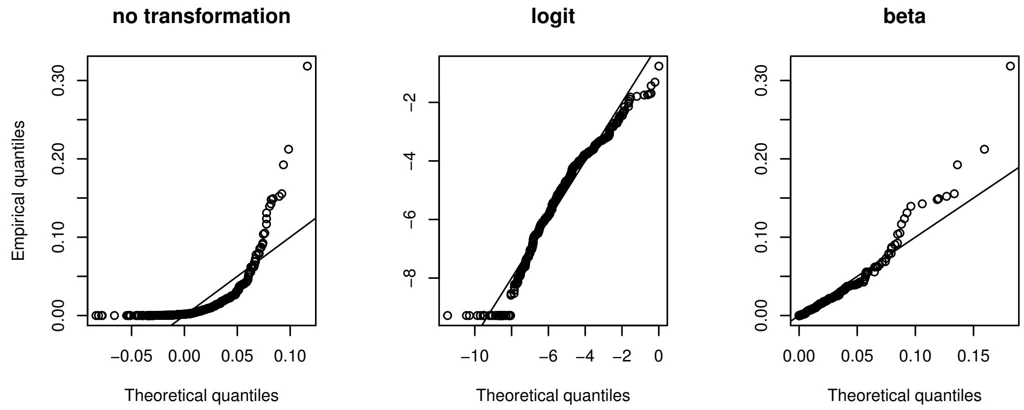

Figure 4.4: Quantile-quantile plots for different transformations/distributions for *rloss*.

and (ii) the relative loss is dimensionless, which means it creates comparable results over space and time without the bias of inflation or varying building costs in different regions (as discussed for floods in Merz et al. (2010) and in the general context of natural hazards by Neumayer and Barthel (2011)). For pluvial floods the majority of the values for *rloss* are typically in the lower range (< 0.4) including cases where water entered the building in such low quantities that it did not cause any direct damage to the building structure (we refer to these cases as zero-loss observations). The bounded outcomes as well as the concentration of values at or close to 0 makes the modeling of *rloss* challenging in the context of (ordinary least squares) regression, which does not account for bounded intervals and therefore may lead to biased estimates. To overcome these limitations the response variable has to be either transformed to map the outcomes to the [0,1] interval or using a regressor where the response variable is assumed to be beta-distributed on the (0,1) interval (Schmid et al., 2013). For the variable selection using machine learning as well as for the stage-damage and multi-variate ensemble model we use the logit-transformation to transform *rloss*:

$$logit(rloss) = log(\frac{rloss}{1 - rloss}) \tag{4.6}$$

This avoids nonsensical predicted values for *rloss* below 0 or above 1. To deal with observations where $rloss = 0$ that would create a transformed value of $-\infty$ we set the values for $rloss = 0$ to the smallest non-zero value in the dataset as suggested by Warton and Hui (2011). This provides more flexibility in the selection of different learning algorithms as machine learning for beta distributed response variables is not yet well established. For the probabilistic multi-variate damage model, where the focus of the model is on prediction, we model *rloss* as zero-inflated beta distribution. The quantile-quantile (Q-Q) plots in Figure 4.4 show the logit-transformation as well as the beta-distribution compared to the untransformed empiric distribution of *rloss*.

Harris County data

Based on a high-resolution pluvial flood map (spatial resolution approx. 30m) containing modeled inundation depth, we construct a multi-variable data set to be used with the proposed uni- and multi-variable probabilistic flood models. The pluvial flood map is provided by *JBA Risk Management* based on model runs covering the period from August 25 2017 to August 28 2017 and represents the maximum water depth per cell in this period. The entire map covers

Table 4.4: Overview of all candidate variables.

Group	Var.	Description	Scale	Range	Missing [%]
Damage	rloss	Relative building structure damage; Normalized with building value	c	0: damage 1: total damage; actual range: 0 - 0.4	-
	dam	Binary building structure damage	b	yes/no	-
	af1*	Basement affected	b	yes/no	< 1
	af2	Ground flood/first floor affected	b	yes/no	< 1
	af3*	Higher floors affected	b	yes/no	< 1
Hazard	wd	Water level relative to the ground level	c	-247cm below ground to 453 cm above ground	5.6
	d	Flood duration	c	1 - 840 h	4.2
	con	Contamination with chemicals, sewage or oil	b	yes/no	4.6
	v	Flow velocity indicator	o	0: still to 6: high velocity	4.6
	rfi1h	Maximum amount of rainfall in 1 hour over the whole storm event	c	15.6 - 141.8 mm	-
Warning	ws1*	Warnung source: Severe weather warning	b	yes/no	1.6
	ws2	Warnung source: Friends, neighbors,family	b	yes/no	1.6
	ws3*	Warning source: National news	b	yes/no	1.6
	ws4	Warning source: Own observation	b	yes/no	1.6
	wt	Early warning lead time	c	0 - 72 h	2.3
Emergency response	em1	Saving documents and valuables	b	yes/no	< 1
	em2	Put movable content upstairs	b	yes/no	< 1
	em3*	Safeguard oil tanks	b	yes/no	< 1
	em4	Pump out water	b	yes/no	< 1
	em5*	Safeguard domestics animals and pets	b	yes/no	< 1
	em6	Protect building against inflowing water	b	yes/no	< 1
	em7	Redirect water on the property	b	yes/no	< 1
Precaution	pre1	Inform about flood hazard/protection	b	yes/no	< 1
	pre2	Participate in flood protection network	b	yes/no	2.5
	pre3	Flood insurance	b	yes/no	2.3
	pre4	Inferior use of exposed floors	b	yes/no	1.6
	pre5	Avoid expensive permanent interior	b	yes/no	2.3
	pre6*	Relocate heating/electricity to higher floors	b	yes/no	3.5
	pre7	Reduce contamination risk (protect oil tank, store chemicals in safe place)	b	yes/no	1.1
	pre8	Improve flood safety of the building	b	yes/no	2.5
	pre9	Install backflow protection device	b	yes/no	1.9

Table 4.4: Overview of all candidate variables.

Group	Var.	Description	Scale	Range	Missing [%]
Experience	fe	Flood experience indicator based on no. of previous floods, previous damage and time since last flood	o	0: no experience to 9: recent experience with loss > 1000 EUR	2.1
	npf	Number of previous floods	c	0 - 5	< 1
Building characteristics	bt1	Building type: Multi-family home	b	yes/no	< 1
	bt2	Building type: Semi-detached house	b	yes/no	< 1
	bt3	Building type: Rowhouse	b	yes/no	< 1
	by1*	Building year: <1924	b	yes/no	< 1
	by2	Building year: 1924 - 1948	b	yes/no	< 1
	by3	Building year: 1949 - 1964	b	yes/no	< 1
	by4	Building year: 1964 - 1990	b	yes/no	< 1
	ht	Oil heating Y/N	b	yes/no	< 1
	bu	Building has basement	b	yes/no	< 1
	bq	Building quality	c	1: very good to 9: very bad	< 1
	bv	Building value	c	88440 - 9682400 EUR	< 1
	nfb	Number of apartments per building	c	1 - 45	1.1
	fsb	Floor space building	c	55 - 4900 sq.m	2.1
	bm1*	Building material: Timber frame	b	yes/no	1.2
	bm2	Building material: Steel-enforced concrete	b	yes/no	1.2
	bm3	Building material: Masonry	b	yes/no	1.2
	bm4*	Building material: Wood	b	yes/no	1.2
	tpi500	Topography index. Relative height of building location compared to surroundings. Radius 500m	c	-17.74 building below to 10.91 above surrounding areas	-
Socio-economic	age	Age of respondent	c	20 - 90 years	3.2
	hs	Number of people living in household	c	1 - 8 person(s)	1.4
	chi	Number of children <14 years in household	c	0 - 3	3.2
	eld	Number of adults >65 years in household	c	0 - 4	2.8
	own1*	Ownership status: Tenant	b	yes/no	< 1
	own2*	Ownership status: Apartment owner	b	yes/no	< 1
	own3	Ownership status: Home owner	b	yes/no	< 1

*Variables have zero or near-zero variance and are not used in the model the the Gulf coast from Corpus Christi, TX to Lake Charles, LA to Huntsville, TX in the north, but only the inundated areas in Harris County, TX are used for this study. As the inundation depth is the result of modeling work and could only partly validated using observations, the provided inundation depths are inherently uncertain. More detailed information on the pluvial flood map are available in the meta data of the flood map and from JBA Risk Management (JBA Risk Management, 2017).

Using the footprint of the maximum extent of flooding from the pluvial flood inundation map, the following additional variables are derived from publicly available data sets: estimate of the inundation duration (d), information on contamination (con), average household size (hs), knowledge of the hazard (pre1), type of building (bt) as well as the value of the building. For an estimate of the inundation duration (d), we use the revised estimated dry times provided by the *Pacific Northwest National Laboratory* (PNNL). The dry times are estimates based on model simulations of a 2-day hindcast and 5-day quantitative precipitation forecast and do not reflect the operational control of dams. The dry times reflect the estimated number of days the water is expected to take from its peak state to a dry state not including base flow conditions (PNNL, 2017).

Point information on the contamination is derived from incidents report data base of the *National Response Center* (NRC) of the United States and filtered for reports in relation to Hurricane Harvey for a report period between August 27 2017 and September 9 2017 (NRC, 2018). Reports not related to water pollution were excluded from the data set. In addition, a data base compiled by the *Sierra Club* containing a collection of national and state level reports from known incidents during Hurricane Harvey were used to validate and/or complement the NRC data (Sierra Club, 2017). In total 98 records are available. We use 2D-kernel density estimation to create a probability map reflecting the probability that an area was contaminated based on the proximity to locations were contamination was reported. The point information of contamination is only interpolated for locations that were within or close to a flooded area (< 30m) and also only within the flooded areas based on the assumption that contaminants (oil, gas, sewage etc.) are only transported through flood water. This approach does not consider flow fields of the surface water or sewage system and is only an estimate of potentially contaminated areas.

To estimate the household size of a building, we use information about the average household size separated by tenants and house owners on the block level, based on the 2016 American Community Survey (ACS) (U.S. Census Bureau, 2016).

The knowledge of the household about flood risk is based on the flood zone information provided by FEMA. The assumptions is made, that households lying within an area with a 1-percent annual chance of getting flooded (Zone A) are aware of the flood risk. This assumption is based on the requirement that property owners have to buy flood insurance in these areas when making, increasing, renewing, or extending a loan (FEMA, 2018*b*).

Information on the type (bt) and value (bv) of the affected buildings can be directly derived from the property data base of the Harris County Appraisal District (HCAD, 2018). For this study we only use private single- and multi-family homes. All commercial or public buildings are not considered and excluded from the data set. For the building value we use the *development replacement cost new less depreciation* (RCNLD) to quantify the current replacement value of each building on the property.

Based on the pluvial flood inundation map we link the flooded areas and other hazard characteristics with the exposed building. This results in a data set with a total of 304 441 affected buildings in Harris County including information on the estimated inundation in centimeter, the flood duration in hours, the probability of the building being contaminated by oil, gas, chemicals or sewage as well as several information on the household size and knowledge about the flood hazard. The modeled relative building losses are multiplied by the RCNLD to obtain loss values in US$. The loss values are validated for the zip code and county level based on reported loss values from FEMA Housing Assistance Program (FEMA, 2018*a*). For validation purposes only the building structure damage of home owners are considered. As only households whose losses are not covered by insurance are eligible to receive funds from FEMA's Housing Assistance Program the validation data might underestimate the total loss when excluding insured losses. However, the underestimation is expected to be minor as FEMA estimated that only 15% of all homes (20% of flooded homes according to estimates by the Consumer Federation of America) in Harris County had flood insurance prior to Hurricane Harvey (Kunreuther, 2018).

4.A.2 SI Materials and Methods

Determining important predictors

For building an effective predictive model, the selection of input variables is a crucial step. However, when the number of variables is large, detailed exploratory analysis of all possible predictors is inefficient and often not feasible (Kuhn and Johnson, 2013). Since input data for loss estimations are scarce and often difficult to obtain, one would strive for a parsimonious loss estimation model, that optimizes the trade-off between number of predictors and predictive accuracy (Grömping, 2009). In this study, we rank all 44 candidate variables (total number of variables is 56, but only 44 considered for variable selection due to near-zero variance of 12 variables) based on the intrinsic variable importance measures of four different predictive models. The respective models are used in a regression context to find the strongest predictors for the level of relative loss (*rloss*) and in a classification context for the presence or absence of loss (*dam*). The variables that show a strong relationship with *rloss* and *dam* respectively are selected to be used as input for the probabilistic loss estimation model.

The supervised predictor selection routine is shown in Figure 4.5. We use the same routine with the same predictors and the same type of models independently to identify the predictors with a strong relationship to *rloss* and *dam* respectively. To increase the robustness of the variable ranking and compensate for recurrence issues frequently appearing in machine learning, the predictor selection is based on the variable importance measures of four different models (Dasgupta et al., 2011). The four models were selected out of a large pool of models provided in the *caret* package (Kuhn, 2008) based on the following criteria: (a) provide inherent variable importance measure, (b) can be used for regression and classification (c) combination of models that is able to detect linear- and non-linear relationships. For the variable importance of non-linear predictors, we use two different non-parametric tree-based ensemble models: conditional inference forests (Strobl et al., 2007) based on an ensemble of independent randomized regression-/classification trees, similar to the random forest model originally proposed by Breiman (2001); and gradient boosting machines based on a stage-wise additive model with correlated trees (Friedman, 2001). To detect predictors with possible linear relationships between the two dependent variables, we use two different penalized linear regression models: the least absolute shrinkage and selection operator (LASSO) with L_1 regularization (Tibshirani, 1996) and Ridge regression with L_2 regularization (Hoerl and Kennard, 1970).

For the classification routine, the proportion of cases with no loss is increased from 9% to 50% through random sampling with replacement to compensate for class imbalance. Each model is tuned individually using 10-fold cross-validation with 10 repeats. That means the dataset is split and resampled to result in 100 individual training and validation datasets.

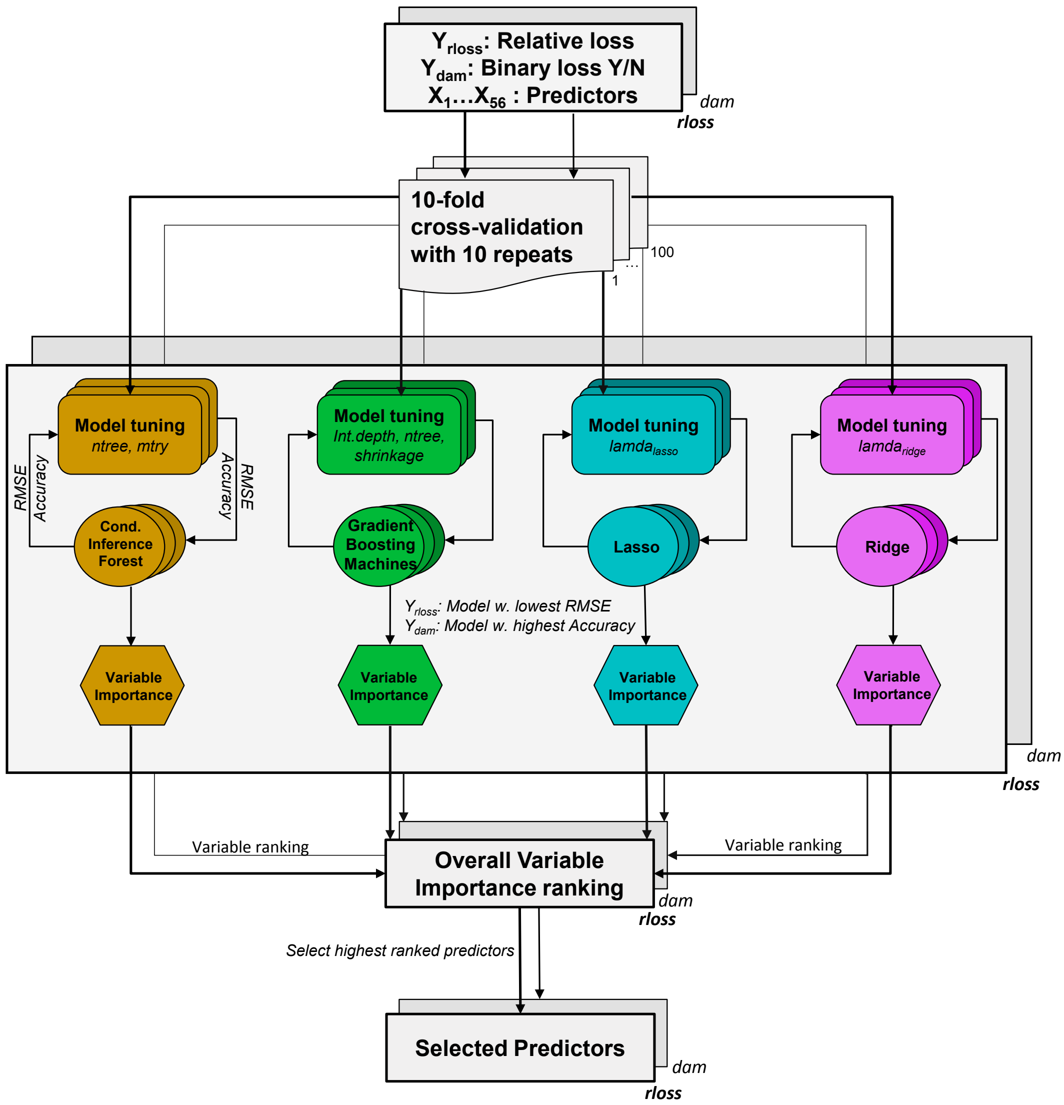

Figure 4.5: Flowchart of the machine learning routine for the variable importance measures of the level of loss (*rloss*) and the the classification of loss/no loss (*dam*). For the variable importance each of the four models are tuned for the lowest RMSE (resp. highest accuracy). The variable importance measures are normalized and each variable is ranked in each of the four models based on their variable importance score. The most important loss influencing variables are selected based on their overall rank(median).

The cross-validation routine is repeated for each tuning configuration and the optimal tuning configuration for each model is selected based on the lowest root mean square error (RMSE) for *rloss* and the highest mean accuracy for *dam*. The model configuration with the lowest RMSE (the highest mean accuracy respectively) are considered as the optimal models and for these models the variable importance of each predictor is determined. The variable importance measures are scaled from 0 (removed from the model) to 100 (most important variable) using unity based normalization to make the scores comparable between the different models. Based on its variable importance score, each variable is ranked from 1 (most important) to 44 (least important) for each variable. The overall rank of each variable is then determined based on the median rank of all four algorithms. The top five variables with the highest overall rank for *rloss* and *dam* are then considered for the actual probabilistic loss model.

Bayesian zero-inflated beta regression

Section 4.3.3 of the main text describes the Bayesian zero-inflated Beta regression model used to develop probabilistic prediction of flood loss. Here we provide details on computation and the priors used.

In Bayesian models involving empirical observations, obtaining analytical solutions for predictions are almost impossible. Hence, we estimate an approximated posterior distribution (Kruschke and Vanpaemel, 2015). Markov Chain Monte Carlo (MCMC) samplers create tens of thousands of parameter replications based on the data generation process to represent the posterior distributions. The probabilistic multi-variate flood loss model is implemented in the *stan* modeling language (Carpenter et al., 2016) using the *brms* package version 3.3.2 (Bürkner, 2017) in R using the No-U-Turn Sampler(NUTS) by Hoffman and Gelman (2014). The MCMC sampler is run with two chains, with 2000 iterations each and a burn-in period of 1000, resulting in a total number of 2000 MCMC samples for each posterior distribution. Model convergence is assessed using the Gelman-Rubin $\hat{R}$ statistic (Gelman and Rubin, 1992), which compares between-chain and within-chain variances to assess MCMC convergence. We obtained $\hat{R} < 1.1$, suggesting good convergence. We also compute the effective sample size of posterior draws, which accounts for the autocorrelation to measure the equivalent number of independent samples (Kass et al., 1998). We confirmed the ratio of effective sample size to nominal sample size to be between 0.999 and 1.001. Bayesian modeling also requires the application of a prior distribution on the parameters applied; Bayes' rule gives

$$p(\theta|y) = \frac{p(\theta, y)}{p(y)} = \frac{p(\theta)p(y|\theta)}{p(y)p(\theta)p(y|\theta)} \propto p(\theta)p(y|\theta) \tag{4.7}$$

and the prior is just the value assigned to $p(\theta)$. Priors are often classified as uninformative, weakly informative, or informative, although these terms are not clearly defined.

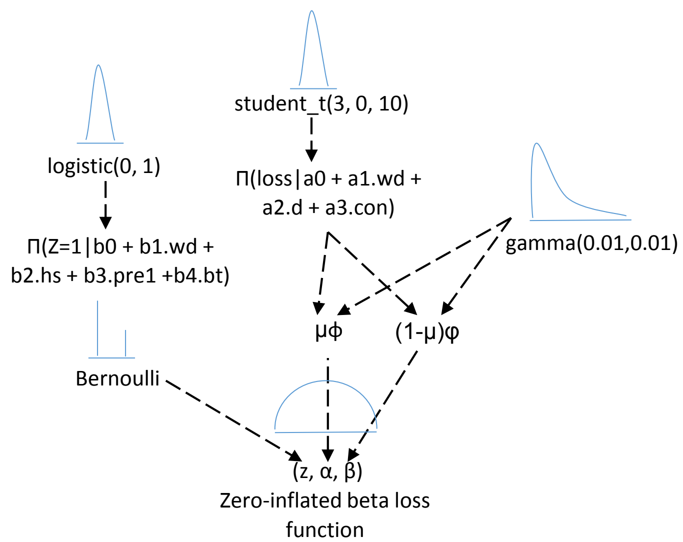

Figure 4.6: Visualization of the zero-inflated Beta model including priors for the Bernoulli and Beta parts.

We applied weakly informative priors, which we define following Gelman et al. (2017) and Simpson et al. (2017) as priors explicitly designed to encode information that applies to a general class of problems without taking full advantage of problem-specific knowledge. In other words, weakly informative priors provide coverage over all parameters which might be plausible. We do not modify the weakly informative priors provided by default in the *brms* package but note that results are not sensitive to alternative specifications of weakly informative priors. These default priors assume that the group-level priors (i.e., γ and β) follow a normal distribution with mean zero and unknown covariance matrix, and assigns an improper flat prior to scale parameters (i.e. ϕ). For further discussion of the priors applied to the unknown covariance matrix we refer the reader to Bürkner (2017).

Models for comparison

We compare the predictive performance of out-of-sample predictions of the uni-and multi-variable *Beta* model with two different model types from the literature: first a stage-damage model based on a root function using the water depth as only predictor as representation of a concept that is widely used in academia and among practitioners to describe the flood vulnerability of a building (Penning-Rowsell et al., 2005; Merz et al., 2013; Scawthorn et al., 2006; Thieken et al., 2008). Root functions are used as reference damage function in (among others) Merz et al. (2013), Schröter et al. (2014) and Wagenaar et al. (2017). Second, a non-linear, non-parametric tree-based model based on the Random Forest algorithm by Breiman (2001), representing the current state of the art for loss models (Schröter et al., 2014; Wagenaar et al., 2017). The root function follows:

$$rloss = c_1 + c_2\sqrt{wd} \tag{4.8}$$

and is fit to the survey data set using Bayesian inference in *Rstan*. Each prediction consists of 2000 Markov-Chain-Monte-Carlo (MCMC) samples from the posterior predictive distribution based on the No-U-Turn Sampler (NUTS) implemented in *Stan* (Hoffman and Gelman, 2014). Priors for c_1 and c_2 are set weakly informative (normal distribution with $\mu = 0$ and $\sigma = 10$) to avoid any bias in the prediction. Before fitting the model *rloss* is logit-transformed to map the bounded outcomes of $rloss \in [0, 1]$ to the whole real line $(-\infty, \infty)$ and to satisfy the assumptions of OLS-regression (i.e. normally distributed residuals).

The *RandomForest* model model uses the original Random Forest algorithm by Breiman (2001) as implemented in the *randomForest* R package (Liaw and Wiener, 2002). The *RandomForest* model is learned with 2000 independent trees ($ntree = 2000$). For each loss prediction of an individual household a predictive distribution is generated by using the mean of the respective terminal node for each of the 2000 trees. The number of trees is set to 2000 to make sure that the predictive distribution of the *RandomForest* model is generated based on the same number of samples as for the posterior predictive distributions of the *Beta* and *Gaussian* models. All multi-variable models are fit using the same 7 variables (see Table 4.1 in the main text, three variables for *rloss*, four variables for *dam*) used in the probabilistic multi-variable *Beta* model. The uni-variable *Beta* and *Gaussian* models are fit as square-root function using the water level as only predictor. The *Gaussian* models are fit using logit-transformed values of *rloss* following the reference function used in Schröter et al. (2014). For the uni-variable *RandomForest* model different split points in the water level are selected based on bootstrap samples of the original dataset; the multi-variable model is fit by randomly selecting two out of six variables at each split ($mtry = 2$).

Model comparison and scoring methods

The predictive performance of the three previously described models are compared using 10-fold cross-validation, where for each iteration 90% of the data are used for fitting/training the models and 10% are used for prediction. For all three models the composition of the folds are the same and each observation in the dataset is used at least once for training and once for prediction. The same dataset described in Section 4.A.1 - *Survey data* is used for all three models. The predictive performance is evaluated in terms of accuracy of the point estimate based on the median of the predictive distribution, using the root mean squared error (RMSE) and mean bias error (MBE); the reliability of the 90% highest density interval (HDI) of the predictive distributions is evaluated using the hit rate (HR) and the dispersion of the interval using the interval score (IS) and mean width of the 90% HDI.

Accuracy of point estimate (median of the predictive distribution) Q_{50i}):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{50i} - O_i)^2} \tag{4.9}$$

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(Q_{50i} - O_i) \tag{4.10}$$

Reliability of the 90% HDI $[Q_{95i}, Q_{05i}]$ of the probability/ensemble sample:

$$HR = \frac{1}{n}\sum_{i=1}^{n} h_i; h_i = 1 = \begin{cases} 1 & , \quad ifO_i \in HDI_{90i} \\ 0 & , \quad \text{otherwise} \end{cases} \tag{4.11}$$

$$IS = HDI_{90i} + \frac{1}{n}\sum_{i=1}^{n}\frac{2}{\beta}(HDI_{90i_{low}} - O_i)|\{O_i < HDI_{90i_{low}}\} + \frac{2}{\beta}(O_i - HDI_{90i_{up}})|\{O_i > HDI_{90i_{up}}\} \tag{4.12}$$

with $HDI_{90i_{low}}$ and $HDI_{90i_{up}}$ marking the upper and lower bounds of HDI_{90i}.

4.A.3 SI Results

Model validation for Hurricane Harvey

Comparing the aggregated modeled predictive distributions with FEMA's Housing Assistance Program, we find that in 103 out of 136 modeled zip code areas, the reported average loss lies within the 90% HDI of the modeled average loss (76%). For the modeled total loss this is true for 112 out of 136 modeled zip code areas (82%). For the total absolute loss for the entire county only the 90% HDI of multi-variable *RandomForest* model covers the reported total absolute loss by FEMA. For the multi-variable *Beta* model the 98% HDI cover the reported loss with a considerably sharper prediction making it the model with the highest IS.

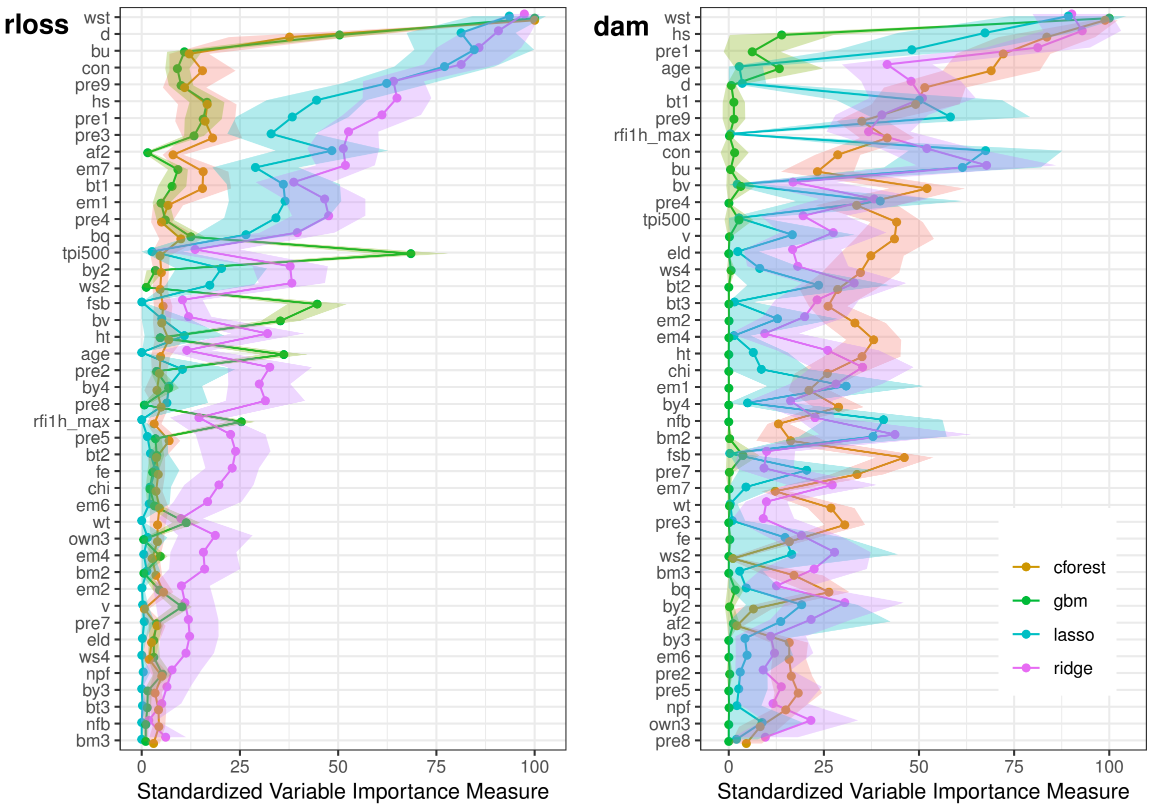

Figure 4.7: Variable importance of the 44 candidate variables using conditional inference forests (cRF), gradient boosting machines (GBM), lasso (LASSO) and ridge (Ridge) regression for the level of loss (rloss) and the classification between loss/no loss (dam). The variable importance values were rescaled for the interval (0,100) using unity normalization. The most important variable for each model was set to 100. A value of 0 means, that the variable was removed from the model (feature selection). The uncertainty bands represent the error of one standard deviation considering all 100 re-sampling rounds.

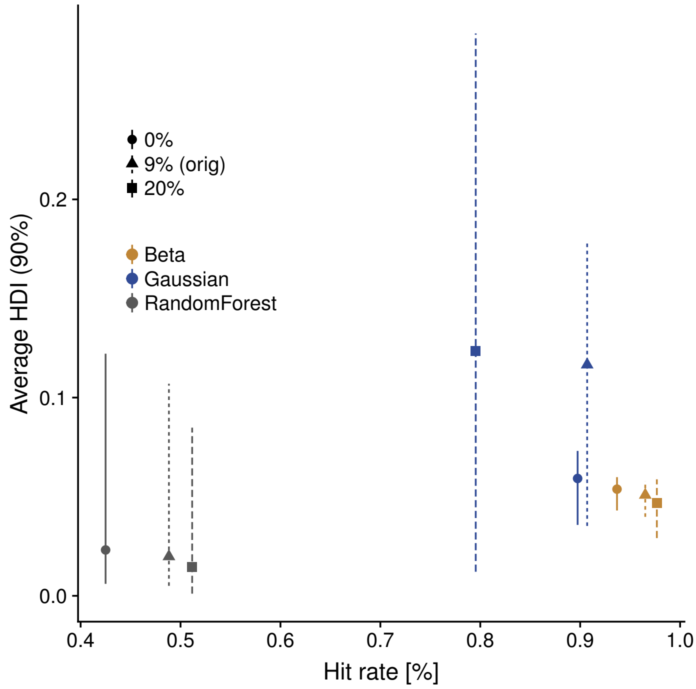

Figure 4.8: Trade-off between reduction in uncertainty and reliability for cross-validated predictions for different uni-variable loss models and different proportions of zero-loss observations in the dataset. Uncertainty is represented as mean width of the 90% HDI for all observations. Reliability is represented as proportion of the out-of-sample observation, which are inside the respective 90 % HDI. Error bars represent the the 90% interval for the HDI width of all out-of-bag predictions.

Acknowledgments: The data collection campaign after the flood event in Münster, Germany in 2014 was supported by the project "EVUS Real-Time Prediction of Pluvial Floods and Induced Water Contamination in Urban Areas" (BMBF, 03G0846B), the University of Potsdam and Deutsche Rückversicherung AG. The data collection campaigns after the pluvial floods in Lohmar and Hersbruck in 2005 were undertaken within the project "URBAS - Urban Flash Floods"; we thank the German Ministry of Education and Research (BMBF; 0330701C) for financial support. Data collection after the pluvial flood in Osnabrück in 2010 were funded by the University of Potsdam, the German Research Centre for Geosciences GFZ, and the Deutsche Rückversicherung AG. Additional financial support is gratefully acknowledged from the German-American Fulbright Commission for V.R.. J. D.-G. thanks the NSF GRFP program for support (Grant DGE 16-44869). We would also like to acknowledge JBA Risk Management, who supported our work by providing the pluvial flood inundation map for Hurricane Harvey. The pluvial flood inundation map from JBA Risk Management is available via the OASIS Hub (`https://oasishub.co/dataset/surface-water-flooding-footprint-hurricane-harvey-august-2017-jba`). The data sets of the flood events in Germany from 2005 and 2010 are available via the German flood damage data base HOWAS21 (`http://howas21.gfz-potsdam.de/howas21/`). The data set from 2014 will be made available via the HOWAS21 data base in June 2023. All other data sets used for the application in Harris County, TX are openly available and cited in the text and SI. Detailed information on all data sets used for this study and how to access them are available in the Supporting Information (Section 4.A.1).

5 Discussion, recommendations and conclusions

5.1 Summary of findings

The overarching objective of this thesis was to improve the estimation of pluvial flood losses through an improved understanding of the factors influencing loss and the underlying uncertainties. Therefore, detailed empirical data about households affected by pluvial flooding were collected and analyzed through a combination of descriptive statistics and machine learning. Based on this information, a new probabilistic modeling approach for pluvial flood losses was developed and successfully applied to a recent pluvial flood event.

Key findings of this thesis are highlighted in the bullet points below. All findings in regard to the research questions defining the structure of this thesis are summarized in the subsequent paragraphs.

Key findings

- The majority of investigated private households were neither aware of nor prepared for pluvial flooding before the respective event occurred.
- The choice of emergency measures undertaken by private households varied with the water depth and whether the aim was to mitigate or prevent losses.
- Besides the water depth, the *degree* of building structure loss was mainly determined by other hazard characteristics (i.e. flood duration and contamination), while the *occurrence* of building structure loss was mainly determined by non-hazard characteristics (i.e. household size, prior knowledge about pluvial flood risk)
- Additional variables in pluvial flood loss models improved the quantification of uncertainties and the detection of zero-loss cases, but not the prediction of point estimates.
- Probabilistic loss models were found to be a suitable approach to account for the high uncertainties in pluvial flood loss estimates
- The choice of response distribution in probabilistic pluvial flood loss models had a strong influence on the reliability of the loss prediction; Models based on a beta distribution led to significantly more reliable loss estimates than comparable Gaussian and non-parametric models.

1. How do private households cope with pluvial flooding?

To analyze how private households cope with pluvial flooding before, during and after an event, detailed information on preparedness, awareness, response and recovery were collected in the form of household surveys following different pluvial flood events in Germany and the Netherlands between 2005 and 2014. The analysis of the household surveys showed that the majority of affected households were not aware of the risk of pluvial flooding before the respective flood event occurred. Even in cases where other parts of the same town had been previously flooded, the majority of households interviewed did not know about the flood risk their own home was facing.

The majority of households perceived precautionary measures as an effective way to mitigate losses. However, households who invested in private precautions both before and after the event focused on measures that facilitate emergency response and recovery, instead of more costly building retro-fitting. Due to the low awareness and the lower uptake in building retro-fitting after the flood, it was concluded that the response shortly before and during an event plays an important role when coping with pluvial floods. Here, the dissemination of early warnings was found to be a critical issue, as only one third of the surveyed households stated that they had received an early warning, even though severe weather warnings with several hours lead time were released in all cases.

2. What explains the differences in preparedness and response between flood-affected households?

Based on the analysis of survey data from flood-affected households following three different pluvial flood events in Germany and one pluvial flood event in the Netherlands, significant differences were found in how households prepared for and responded to pluvial flooding.

While a relatively greater number of households who were previously affected by flooding or had knowledge about the flood risk of their home had implemented precautionary measures, it could not explain the difference in the absolute number of measures implemented. Here, the significantly lower number of precautionary measures implemented in the Netherlands compared to the German case studies indicates that other factors such as regional differences in the risk perception might explain the difference.

In regard to the emergency response, it was found that households perform different emergency measures depending on the flood magnitude. For events where average water levels were higher, households predominantly focused their emergency response on reducing losses, while during events with lower water levels households primarily implemented measures with the aim of avoiding losses, such as sealing windows or basement shafts.

3. Which factors influence pluvial flood loss to private households?

Using both descriptive statistics in Chapters 2 and 3 and machine learning in Chapter 4, different variables were found to influence different aspects of pluvial flood loss incurred by private households.

While in all analyses water depth was found to be the most important loss-influencing factor, the univariate analysis of different pluvial flood events showed that receiving an early warning and consequently undertaking emergency measures reduces losses to building contents. Losses to the building structure, on the other hand, were found to be mainly influenced by additional flood characteristics such as the duration of the flood.

The machine learning analysis revealed that the drivers for the occurrence of building structure loss and the drivers for the degree of loss to the building structure are different, indicating different damaging mechanisms. Here, only the variables influencing the degree of loss confirmed findings from the previous univariate analysis, where the increase in building structure loss was found to be explained best by additional flood characteristics such as flood duration or contamination of the flood water. The occurrence of building structure loss, on the other hand, was found to be influenced predominately by non-hazard characteristics, such as the size of the household and whether or not the household had prior knowledge about the risk of pluvial flooding. It was concluded that differences in variables between different aspects of pluvial flood loss should be taken into account when quantifying pluvial flood losses.

4. Can implementing these factors in loss models improve the quantification of pluvial flood losses?

To analyze whether using variables in addition to the water depth could improve the quantification of pluvial flood losses, the predictive performance of probabilistic uni- and multi-variable loss models was evaluated using cross-validation. The uni-variable models used the water depth as the single most important variable, while the multi-variable models additionally used five of the most important variables detected by the preceding machine learning analysis.

Using additional predictors, the probabilistic quantification of pluvial flood losses was improved in two ways: First, for spatially aggregated estimates, multi-variable models provided a consistently better balance between sharpness and reliability, thus reducing the risk of incorrect predictions. Second, additional variables improved the detection of cases in which water entered the building but did not cause any loss to the structure, thus reducing the bias in the loss estimates.

Comparing the prediction errors of point estimates instead of predictive distributions for pluvial flood losses, only a minor non-significant improvement between uni- and multi-variable loss models was found. Therefore, probabilistic loss models are needed to take advantage of the information from additional variables when estimating losses from pluvial flooding.

5. What influences the reliability and uncertainty of pluvial flood loss models

To understand what influences the reliability and uncertainty of building structure loss estimates, a fully probabilistic modeling approach was applied for the first time in pluvial flood loss modeling.

Different probabilistic loss models were trained and evaluated with regard to reliability, meaning the ability of the predictive distribution to cover the actual observed loss, and uncertainty, meaning the width of the highest-density interval of the predictive distribution. It was found that the uncertainty and reliability of the continuous predictive distributions of different loss models vary considerably depending on the use of additional predictors, the choice of response distribution, the ability of the model to account for zero-loss cases and the spatial scale of the analysis.

With their ability to significantly reduce uncertainties compared to the widely used Gaussian stage-damage functions without sacrificing the reliability, the use of multi-variable pluvial flood loss models based on a zero-inflated beta distribution is recommended for the quantification of pluvial flood losses on both the object and city scales.

5.2 Discussion and recommendations for further research

During the analysis of how private households cope with pluvial flooding as well as the development and application of a novel probabilistic pluvial flood loss model, several aspects emerged which require discussion in a broader context. The discussion follows the study design used in this thesis (see Figure 1.2 in Chapter 1) starting with the *data collection and data analysis* followed by the *model development* and closes with the *model application*. Each section discusses the potentials and limitations of the approach taken in this thesis, including unresolved questions that provide directions for further research.

5.2.1 Data on pluvial flood impacts

To analyze how private households cope with pluvial flooding and which factors influence pluvial flood losses, detailed information on the household level about both impacts and resistance parameters is needed.

In this thesis, detailed empirical data on how pluvial flooding affects private households were collected using structured web and telephone surveys. This approach was chosen for its ability to overcome many limitations identified in previously used data sets and data sources (see Chapter 1), especially in regard to an insufficient level of detail, incomplete information, and issues to distinguish between different causes for water-related losses.

Besides method-specific pitfalls such as response bias or data entry errors, discussed in detail in Chapter 3, the high level of detail of the survey data allowed for a quantitative in-depth analysis of pluvial flood vulnerability of private households, which had not been possible with previous data sources. One challenge that was discovered during the data collection process and that was found to be true for other available empirical data sets on pluvial flooding was the focus on large events, as most pluvial flood events are too small in terms of both spatial extent and monetary loss to gain enough attention to be reported. Smaller events, such as the pluvial flood in Amsterdam investigated here, should not only be considered in future data collection campaigns because there are indications that small but frequent pluvial flood events make up a considerable share of the total annual loss (Einfalt et al., 2009; Ten Veldhuis, 2011; Moftakhari et al., 2017), but also because the coping strategies of private households were found to be highly dependent on the flood magnitude. Ignoring these differences can lead to misjudgments regarding the coping capacity of private households and, consequently, the expected losses from pluvial flooding as well.

While the survey approach used in Chapters 2 and 3 can be used to collect data from events of all sizes, the costs and effort, especially in conducting computer-aided telephone interviews, requires that events are large enough to gain a sufficient number of observations per survey campaign. The open-source web survey approach presented in Chapter 3 significantly reduces the costs and effort per interview and is therefore recommended for future data collection campaigns around smaller events. However, it still requires the detection of (small) pluvial flood events that can be surveyed.

Here, a stronger collaboration between research, practice and public administration dealing with pluvial flooding is needed to support the data collection and extension of the existing data bases on pluvial flood impacts. The introduction of high-level standards and platforms for local administrations to report on pluvial flood events in their communities is particularly recommended, as it can give a more complete picture of the temporal and spatial occurrence of pluvial flooding. This information is not only important for researchers, but is also highly relevant for decision makers, e.g. when evaluating the cost-effectiveness of risk reduction measures. Based on the open-source web survey tool for pluvial floods from Chapter 3 such an event data base can then be enhanced with a semi-automatized collection of detailed survey data.

In addition to a better reporting and collection of new data on pluvial flood impacts, already available data such as detailed exposure or loss information should be used more efficiently. This requires a stronger commitment to existing open data policies and portals from key stakeholders, including researchers, emergency responders, local and federal authorities and the insurance industry. The example of a US case study in Chapter 4, where a highly detailed input data set was constructed entirely from openly available datasets, highlights the need for federal, national and local authorities in Germany and the EU to catch up. A better availability of data sets through open data portals would not only facilitate the exchange and use of already available data but could also help to increase links between the groups mentioned to improve pluvial flood management practices.

A further exploitation of new data sources and sensors, such as volunteered geographic information, call record data or high-resolution remote sensing imagery, can then be used to complement existing data e.g. regarding human activities before, during and after pluvial flood events (Ford et al., 2016).

5.2.2 The human factor in pluvial flood loss estimation

To investigate how private household's awareness, preparedness and response influences the losses caused by pluvial flooding, detailed data on how households behave before, during and after a flood event were analyzed. While losses from any type of flood are the result of different flood impact and resistance parameters, the resistance is typically reduced to building properties in most loss estimation approaches. In the case of pluvial flooding it was shown that this approach falls short, as the combination of lower water levels and a low preparedness of households puts loss-mitigating actions by individuals shortly before, during and after a pluvial flood event in a prominent position in the loss-generating process.

However, to measure both the direct and indirect influences of human actions on flood losses is challenging. Whether or not an individual takes a particular action and how effective this action is in mitigating or preventing losses is inherently uncertain and depends on a large number of additional factors. This requires a modeling strategy in which (i) the influence of human actions on flood losses can be simplified and represented by measurable variables, and (ii) the low predictability and variability of these actions can be accounted for. In this thesis, indicators that are expected to affect human actions, such as the age or risk awareness of an individual are used in combination with a fully probabilistic approach based on Bayesian inference to quantify the uncertainties associated with these actions.

Both the consistently higher importance scores of these indicators compared to most building variables (see Table 4.1) and a better representation of uncertainties in the loss estimates demonstrate the potential to consider human actions in flood loss models. At the same time, the only minor improvement in predictive performance in point predictions shows that the use of indicators can only partly reflect the influence of human actions on losses from pluvial floods.

While further research is needed on factors that are able to better represent the influence of human action on flood losses, Bayesian inference used in this thesis has shown to be a suitable modeling approach for including human factors in loss models. This is not only due to its ability to consistently represent the uncertainties of human actions, but also because Bayesian inference allows the modeler to enhance or even replace empirical data with probabilities of human activities that are conceivable but cannot be directly derived from available empirical data sources through the use of priors. This includes giving a prior probability of that an individual will undertake a loss-mitigating action when the individual has knowledge about the risk of pluvial flooding, but also allows for the proposed implementation of theories from other research fields such as behavioral sciences and behavioral economics (Aerts et al., 2018).

To account for the high dynamic of many human actions, future developments in pluvial flood loss modeling could extend the approach taken in this thesis by combining Bayesian with agent-based models. Such approaches have been successfully used in water management applications (Pope and Gimblett, 2015), but agent-based models also receive increasing attention in flood risk research (Dawson et al., 2011; Haer et al., 2017).

With more detailed data on human behavior before, during and after pluvial flood events becoming available through active and passive sensors such as web search engine inputs and social media usage (Feng and Sester, 2018), these models can be further refined and validated to better represent the human influence on losses for an improved loss estimation.

5.2.3 Probabilistic loss models for pluvial floods

For an integrated risk management, but also to guide response and recovery following a flood event, it is necessary to reliably quantify the losses from pluvial flooding. However, prediction errors in flood loss estimates are generally high, especially on small spatial scales (i.e. neighborhoods or individual buildings), which are needed when quantifying losses from pluvial flooding. The use of both additional loss-influencing predictors (Thieken et al., 2008; Van Ootegem et al., 2015; Grahn and Nyberg, 2014) and more complex model types such as tree- or network-based models (Merz et al., 2013; Vogel et al., 2012; Hasanzadeh Nafari et al., 2016; Wagenaar et al., 2017) has so far led to only a minor reduction in prediction errors. The pluvial flood loss model(s) developed in this thesis are no exception, as the errors in point predictions are high.

While this severely impairs the validity of loss estimates, most flood loss models do not disclose how certain their estimates are (Scawthorn et al., 2006; Emschergenossenschaft & Hydrotec, 2004) or communicate the model uncertainties in an inconsistent way, complicating the comparison between models (Chatterton et al., 2014; Wagenaar et al., 2016; Dittes et al., 2018). Therefore, this thesis proposes a fully probabilistic modeling approach based on Bayesian inference for a robust estimation of pluvial flood losses, where predictions are provided in the shape of uncertainty distributions instead of point estimates. While the probabilistic loss models developed in this thesis do not directly reduce the errors of point predictions, the predictive distributions of loss estimates give information on how well the models describe the uncertainties of the prediction, which has so far not been considered in previous approaches.

The comparison between different probabilistic loss models in Chapter 4 shows that previous assumptions on log-normally distributed uncertainties (Merz et al., 2004) significantly overestimate the uncertainties in the upper tail of the distribution, making the beta distribution (Egorova et al., 2008) the recommended choice for pluvial flood loss estimates on the building level. The flexibility of the presented framework allows uncertainties to be quantified independently of the model type, input data scale or uncertainty distribution. This includes the use of mixture distributions to combine the degree of loss and the occurrence of loss into one prediction as shown in this thesis, but the implementation of probabilistic versions of existing SDFs or complex non-linear and multi-variate models can also be realized.

This is an important advantage compared to previous probabilistic loss models, in which the quantification of uncertainties is tied to a specific model type (i.e. tree-based models) (Kreibich et al., 2017) or requires the transformation of inputs (Vogel et al., 2012) and is an important step in facilitating a postulated shift towards probabilistic loss models (Schröter et al., 2014). The comparison with probabilistic models using tree-based bootstrap approaches has further shown that the short tails of non-parametric uncertainty distributions severely reduce the reliability of loss estimates on the building level and therefore require the modification of commonly used tree-based algorithms as shown by Sieg et al. (2019).

Unlike previously developed probabilistic loss models (Vogel et al., 2012; Schröter et al., 2016), the variable selection and model parameterization in this thesis are separated in two independent steps. In the first step, loss-influencing predictors are screened for their predictive performance using an ensemble of machine learning algorithms before using the strongest predictors for the parameterization of the probabilistic loss model in the second step. This approach increases the robustness of the variable selection, which has been a limitation in previous data mining approaches, where the variable selection is very sensitive to the type and distribution of the data (Strobl et al., 2007; Merz et al., 2013; Schröter et al., 2014).

However, as there are high uncertainties not only in the loss predictions but also in the variable selection, the detection of loss-influencing variables in future models could be further improved by extending the variable selection process with probabilistic Bayesian approaches. Being an active area of research, the use of regularizing priors (i.e. horse priors) has recently emerged as an approach to increase the robustness of the variable selection process in sparse probabilistic models (Carvalho et al., 2009; Piironen et al., 2017).

As this thesis is focused on the quantification of uncertainties in loss models, additional sources of uncertainties, such as from measurement errors or uncertainties from previous modeling steps, are at this point not considered in the loss estimate. This limitation also applies to the application of the developed loss model presented in Chapter 4, where the inundation depths from hydraulic model outputs are used to estimate the exposed objects and their losses. While these outputs are subject to uncertainties themselves (Freni et al., 2010; Zhou et al., 2012), the deterministic results and lack of uncertainty information in the hydraulic model output did not allow those uncertainties to be propagated into the loss estimate. For a further improvement of pluvial flood risk assessments, it is therefore recommended to use not only probabilistic loss models, but an entirely probabilistic model chain, as it allows for consistent propagation of the uncertainties of the outputs from each model component to the subsequent modeling step for a more realistic representation of uncertainties in all model outputs including the loss estimates. A fully probabilistic approach would also allow for a consistent sensitivity analysis of pluvial flood losses which has shown to be challenging using frequentist modeling frameworks (Tate et al., 2014; Freni et al., 2010).

5.2.4 Transferability and scalability of pluvial flood loss models

As uncertainties in loss estimates are high and validation data scarce, it is often unclear how reliable loss estimates are when models are spatially or temporally transferred without validation (Cammerer et al., 2013). The low number of pluvial flood models and the unknown transferability of pluvial flood models together with the high requirements for input data has so far led to an exclusion of pluvial flood risk in large scale pluvial flood risk assessments and trend analysis (Ward et al., 2013; Paprotny et al., 2018).

In Chapter 4 of this thesis, the probabilistic loss model trained with data from Germany is applied to a recent pluvial flood event in Houston, TX (USA). As the validation on both the zip code and county levels showed that the developed model performs well despite very different regional characteristics between the training and application areas, it raises the question to what extent the presented pluvial flood loss model can be transfered and scaled to support an extensive estimation of pluvial flood risk in urban areas.

While it is difficult to draw conclusions about the general transferability of the developed model from one case study, several findings from this thesis and previous studies support the assumption that a successful model transfer to other regions is possible.

First, the analysis of important loss-influencing variables has shown that building properties such as the building material, which are probably the biggest difference between the two regions, only play a minor role in explaining both the degree and occurrence of building structure loss. While differences between building properties in the training data set do not necessarily reflect those in the application area, it indicates that building properties may generally play a minor role in pluvial flooding.

Second, the training data set is quite heterogeneous, containing different flood events with different event magnitudes in different regions and different building types and town sizes. Here, previous studies on river floods have shown that the performance of transfered models can be significantly improved when training data sets with a high heterogeneity are used (Wagenaar et al., 2018).

Third, based on the comparison between uni-variable and multi-variable models in Chapter 4, it can be concluded that using additional predictors besides the water depth in loss models increases the transferability of loss models through a more realistic representation of uncertainties, confirming findings from similar studies on river flooding (Schröter et al., 2016). In the case of the multi-variable, zero-inflated beta regression model developed and applied in this thesis, additional variables support a model transfer not only by improving the representation of uncertainties, but also through an improved detection of zero-loss cases, which can reach a high rate in areas where water levels are low (see Figure 4.2). In this regard, the probabilistic mixed distribution approach in this thesis also helps compensate for the uncertainties coming from inundation maps, which would otherwise lead to an overestimation of losses when large areas are inundated with low water depths (see multi-variable Gaussian model in Figure 4.3).

While further validation and case studies are necessary, the potentially high transferability of the model developed here could be used in future studies to complement existing large-scale flood loss models for river and coastal flooding. The continental approach by Guerreiro et al. (2017) for European cities and by Wing et al. (2018) for the conterminous USA, generating extensive high-resolution pluvial flood maps in urban areas, could be extended with the loss model developed in this thesis to include estimates of building structure losses to private households. While both the uncertainties and the demand for input data are high, the flexibility of the Bayesian framework used to develop the probabilistic multi-variable loss models allows for a consistent quantification and propagation of uncertainties as well as an intuitive means of local calibration through the use of priors, making the presented model highly scalable. While the increased availability of high-resolution data sets and computational power is making high-resolution pluvial flood loss estimation feasible, more research on the transferability of pluvial flood loss models is necessary to evaluate the robustness of such an approach.

5.3 Conclusions

This thesis has improved the estimation of losses from pluvial flooding to private households on the basis of an increased understanding of the loss-influencing factors and processes. Losses from pluvial flooding are the result of complex, small-scale interactions between the flood impact and the ability of a household to resist the impact. Detailed, household-level data sets linking impact with resistance variables are necessary to systematically analyze these interactions, which are not visible in aggregated or lumped data sets.

Although households without prior flood experience are mostly neither aware of nor prepared for pluvial flooding, losses can frequently be prevented when water levels are low and households respond timely and efficiently. Better information about the risks of pluvial flooding, improved early warning systems and a better dissemination of warnings are needed to improve the ability of private households to mitigate or prevent losses. This in turn requires a reliable quantification of the current and future risk of pluvial flooding.

Simple, deterministic water depth-loss relationships developed for estimating losses from large-scale river or coastal flooding neglect both small-scale differences in the damaging processes and the ability of a household to mitigate or prevent losses, resulting in highly uncertain loss estimates when applied to pluvial flooding. The use of additional resistance variables in loss models improves the detection of households that are able to prevent losses, yet a considerable part of the variability in losses on the building level remains unexplained.

Complex models in the shape of Bayesian multi-variable mixed distribution models combine an improved detection of cases where losses could be prevented with a probabilistic framework for a consistent quantification of the remaining uncertainties. Using continuous predictive distributions, which provide a range of probable losses instead of a single point estimate, leads to significantly more robust loss estimates. The shape of the predictive distribution predominantly defines the reliability of the loss estimate on the building level and must be chosen carefully to avoid an over- or underestimation of uncertainties. The mix of Bernoulli and beta distributions has a high flexibility in terms of shape and therefore better represents the uncertainties of building-level losses than previously used normal or log-normal distributions.

For the estimation of pluvial flood losses on the building-level, an increasing number of high-resolution data sets are available. In combination with an increased robustness of probabilistic loss estimates, this allows for a reliable high-resolution quantification of losses and a seamless scaling of risk assessments for pluvial floods. Many of these new data sets focus on increasing the level of detail of building properties, which hardly have an influence on building structure loss from pluvial flooding. Instead, more focus should be put on how detailed and dynamic data on the individual coping capacity and behavior of households can be more efficiently collected and used in loss models. While more detailed information on building properties is still needed to e.g. determine the value of a building or discover potential entry points of flood water, this information is not expected to directly improve the loss estimates for pluvial floods.

In conclusion, I recommend data-driven, probabilistic, building-level loss models as the appropriate tool for estimating pluvial flood loss to private households. This is not only because the required data, modeling techniques and computational power are becoming increasingly available, but because it allows to reliably quantify the risk from pluvial flooding on the spatial scale on which this flood type occurs.

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