AGU ADVANCING EARTH AND SPACE SCIENCE

Water Resources Research

RESEARCH ARTICLE
10.1029/2019WR025943

Key Points:
- Survey data of flood-affected households show different concurrent flood types, undermining the use of a single-flood-type loss model
- Thirteen variables addressing flood hazard, the building, and property level preparedness are significant predictors of the building loss ratio
- Flood type-specific models show varying significance across the predictor variables, indicating a hindrance to model transferability

Supporting Information:
- Supporting Information S1

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Citation:
Mohor, G. S., Hudson, P., & Thieken, A. H. (2020). A comparison of factors driving flood losses in households affected by different flood types. *Water Resources Research*, *54*. https://doi.org/10.1029/2019WR025943

Received 8 JUL 2019
Accepted 9 MAR 2020
Accepted article online 13 MAR 2020

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

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Abstract Flood loss data collection and modeling are not standardized, and previous work has indicated that losses from different flood types (e.g., riverine and groundwater) may follow different driving forces. However, different flood types may occur within a single flood event, which is known as a compound flood event. Therefore, we aimed to identify statistical similarities between loss-driving factors across flood types and test whether the corresponding losses should be modeled separately. In this study, we used empirical data from 4,418 respondents from four survey campaigns studying households in Germany that experienced flooding. These surveys sought to investigate several features of the impact process (hazard, socioeconomic, preparedness, and building characteristics, as well as flood type). While the level of most of these features differed across flood type subsamples (e.g., degree of preparedness), they did so in a nonregular pattern. A variable selection process indicates that besides hazard and building characteristics, information on property-level preparedness was also selected as a relevant predictor of the loss ratio. These variables represent information, which is rarely adopted in loss modeling. Models shall be refined with further data collection and other statistical methods. To save costs, data collection efforts should be steered toward the most relevant predictors to enhance data availability and increase the statistical power of results. Understanding that losses from different flood types are driven by different factors is a crucial step toward targeted data collection and model development and will finally clarify conditions that allow us to transfer loss models in space and time.

1. Introduction

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

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

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

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

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

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

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

2. Materials and Methods

2.1. Database

In order to reconstruct how different flood types cause a monetary loss at the property level, flood loss assessment must rely on data, either from measurements (either directly observed or via experimentation or surveys of those directly affected) or from expert judgment. In order to collect widespread information on flood losses that occurred in the wake of widespread flood events, survey data from those directly affected are the most suitable choice. To this end, a data set was constructed from surveys conducted via computer-aided telephone interviews (Thieken et al., 2017) in the aftermath of large flooding events in 2002, 2005, 2006, 2010, 2011, and 2013 in Germany (Table 1). The motivation behind these surveys was to better understand the direct impacts suffered by those affected (Thieken et al., 2017). The surveys covered a range of topics, from hazard characteristics to preparedness, aimed at developing flood loss models and forensic analyses (Kreibich, Thieken, et al., 2017) and had been previously presented, for example, in Kienzler et al. (2015), Thieken et al. (2005), Thieken et al. (2007), Thieken, Bessel et al. (2016), and Vogel et al. (2018). Each survey underwent adaptations for the sake of better clarity for respondents but maintained comparability over time. Therefore, this study can be considered to use repeated cross-sectional data.

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

In Table 1, we present the number of surveyed data points as assigned to a particular flood type. In the 2002 survey, the responses were assigned to flood types according to how the water entered the house as reported by the respondent, the topography, and the proximity of the house to a river or levee. More than one flood type could have taken place on the same property. However, the one considered to be the most damaging

Table 1
Number of Interviewed Households in Time and Space per Flood Type

Flood type	Levee breach (n = 810)	Riverine (n = 2,509)	Surface water (n = 447)	Ground water (n = 652)	Total (n = 4,418[a])
Year					
2002	302	796	258	329	1,685
2005	23	200	27	52	302
2006	2	133	10	11	156
2010	86	262	67	18	433
2011	3	158	16	37	214
2013	394	960	69	205	1,628
Federal State					
Brandenburg	0	5	0	0	5
Mecklenburg Western Pomerania	0	1	1	0	2
Saxony	389	1,134	158	209	1,890
Schleswig-Holstein	1	15	1	0	17
Saxony-Anhalt	218	428	70	170	886
Thuringia	27	144	9	32	212
Lower Saxony	5	96	47	30	178
Hesse	0	5	2	0	7
North Rhine-Westphalia	0	6	1	2	9
Rhineland Palatinate	1	47	9	7	64
Baden-Wurttemberg	0	54	6	5	65
Bavaria	169	574	143	197	1,083

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

was taken as representative of the respondent's experience. Still based on the 2002 data, the order, from most to least damaging flood type, was set as follows: levee breaches, riverine floods, surface water floods, and rising groundwater floods, after statistical analysis of all cases (Hristova, 2007). In the following events (i.e., after 2002), the flood type was assigned based on what the respondents attributed flooding on their property to, and the most damaging type was established if more than one type could be assigned. In the process of assigning flood types, the riverine and surface water flood types were more difficult to separate, compared to groundwater- or levee breach-affected households. While our database included data from six different years, there was a dominance of observations from the largest events in 2002 and 2013. Twelve out of the 16 federal states in Germany were represented in the database. However, there was a dominance of data from Saxony, Bavaria, and Saxony-Anhalt, reflecting the most affected states, while some states had very few observations (e.g., Brandenburg; Table 1).

The surveys addressed several aspects of the flood events: characteristics of the affected building, the presence and characteristics of the warning as perceived by the surveyed residents, their flood experience and preparedness, socioeconomic information of the household, demographic information of the household, the hazard intensity at the property, and the losses to the building and its contents. The data set was diverse not only in its aspects but also in the format of answers, with continuous (metric), ordered, and nominal (nonmetric) scales −12, 11, and 8 potential predictors, respectively. Ordered variables were treated as continuous variables since the Likert-scales only verbally expressed the meaning of the end points, not of the intermediate steps. These predictors were selected from the larger database after previous analyses indicated them as factors influencing direct monetary loss (Kreibich et al., 2011; Merz et al., 2013; Thieken et al., 2005; Thieken et al., 2008; Vogel et al., 2018) and with a reasonable balance between different aspects—hazard, preparedness, and building and socioeconomic characteristics, with the addition of administrative regions within Germany. We can reasonably group the variables as shown in Table 2.

Most of the surveys were completed around 10 months after the flood. One of the reasons for not surveying directly after the event is to allow the respondents to recover and become fully aware of the repair costs involved. In addition, a later survey is more likely to capture second-order effects, for example, in the case of oil contamination. This provides a more complete view of the damage and the involved repair costs.

2.2. Methods

The key objective of this study is to investigate whether different flood types display distinct loss-generating processes. Significant differences in which variables may be important, as well as their magnitude of

Table 2
Variables Used in the Study Grouped by Aspect (Adapted From Vogel et al. [2018])

Variable	Description	Range and reference	Type (3)
Hazard Characteristics			
Water Depth	Relative to ground level	−248 to 1,328 cm	C
Duration[a]	Duration of how long flood water was inside the house	1 to 1,440 hr	C
Velocity	Rank scale of flow velocity: 0 = no flow to 6 = very high velocity	0–6	O
Contamination	Indicator of contamination in the flood water: 0 = no contamination to 2 = heavy contamination (e.g., by oil)	0–2	O
Warning			
(Early) Warning Lead Time[a]	Time between the warning and being hit by the water	0 to 336 hr	C
Perceived Knowledge About Self-Protection (Quality of Warning)	Rank scale: 1 = knew exactly what to do to 6 = did not know what to do	0–6	O
Warning Information	Indicator of information provided in the warning messages assessed with regard to supporting loss mitigation (Thieken et al., 2005)	0 to 16	O
Warning Source	Indicator of source warning: 0 = no warning to 4 = warning from official agency (Thieken et al., 2005)	0 to 4	N
Gap Between Warning and Action	Gap time between receiving the warning and starting to act	0 to 336 hr	C
Preparedness			
Emergency Measures	Indicator weighting emergency measures performed effectively (Thieken et al., 2005)	0 to 17	O
Precautionary Measures	Indicator of overall precaution at the property with 0 = no precaution to 2 = very good precaution (Thieken et al., 2008)	0 to 2	O
Perceived Efficiency of Precautionary Measures	Rank scale: 1 = measures could reduce loss efficiently to 6 = measures could not reduce loss at all	1–6	O
Flood Experience Class	Indicator of previously experienced floods with 0 = no previous experience to 4 = recent and/or repeated experience (Thieken et al., 2005)	0 to 4	O
Awareness of Flood Risk	Knowledge that the residence was located in a flood-prone area	yes or no	N
Insurance Cover	Flood insurance coverage before the event	yes or no	N
Building Characteristics			
Ownership	Categorized: owner of the building, owner of the flat, or tenant	3 classes	N
Building Type	Categorized: detached home, semi-detached home, or apartment building (with several flats)	3 classes	N
Number of Flats	Number of flats in the building	1 to 40	C
Building Quality	Rank scale: 1 = very high quality to 6 = very low quality	1–6	O
Building Value (1)[a]	Asset value inferred through standardized insurance practices	98.5 10^3 to 21.2 10^6 €	C
House or Flat Area[a]	Inhabitable area of the house or flat	20 to 1,200 m^2	C
Building Area[a]	Floor space of the whole building	32 to 18,000 m^2	C
Cellar	Presence of a cellar	yes or no	N
Household and Socioeconomic Features			
Age	Age of the interviewed person	16 to 99 years old	C
Household Size	Household size	1 to 20 persons	C
Children	Number of household members under 14 years old	0 to 6	C
Elderly	Number of household members over 65 years old	0 to 9	C
Income Class	Categorized: from 11 = "> 500 Euros" to 16 = "3,000 Euros and up"	11–16	O
Socioeconomic Status	Categorized: 1 = lower class to 4 = upper class (Plapp, 2003 apud Thieken et al., 2005)	1–4	O
Others			
Region (2)	Grouping of federal states (see footnote 2)	3 classes	N
Year	Year of the event	2002, 2005, 2006, 2010, 2011, and 2013	N
Loss (Ratio)			
Building Loss	Reported losses to the building (adjusted to 2013 prices)	0 to 1.1 10^6 €	C
Building Loss Ratio	Ratio between absolute monetary loss and estimated building value	0% to 100%	C

Note. (1) Building values were estimated through standardized values leading to a high correlation with the building area, and therefore, this variable was dismissed. (2) The German Federal States were grouped into three regions: South (Bavaria and Baden-Wurttemberg—Danube and Rhine river basins); former East German states; and North and West (e.g., Rhine, Ems, Weser, and lower Elbe river basins). (3) C = Continuous; O = Ordered; N = Nominal. For some ordered variables, only the endpoints were given, so the variables can be considered as an interval scale. Ordered variables are treated as continuous.
[a]Variable was log transformed for the regression framework due to a high skew, and its values are strictly greater than zero

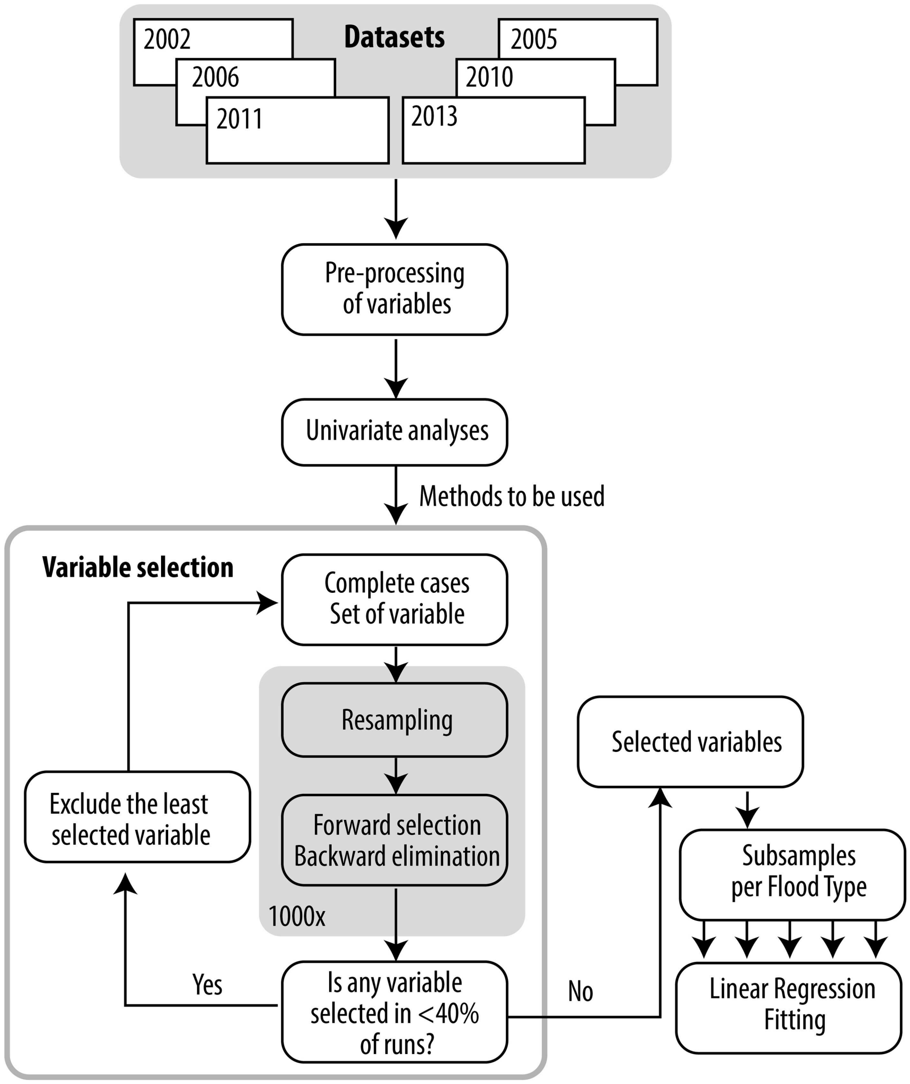

Figure 1. Sequence of analyses employed in this study.

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

In order to address this complexity, we divide our analysis and approach into two stages (Figure 1). The first set is a series of preliminary tests based on univariate assessments. The purpose of the univariate assessments is to investigate the suitability of the linear regression assumptions and to compare the homogeneity of subsamples across flood types by investigating possible predictors individually. This step focuses on and guides our attention to suitable methods and variables for the second step of the analysis.

The second step of the analysis is the employment of a regression model framework to infer possible relationships between important variables and the building loss ratio. A multivariable regression is selected, as it is capable of accommodating several independent variables of multiple formats (metric and nonmetric) and one metric dependent variable, and can be used for both prediction and explanatory purposes (Hair et al., 2019). The regression framework first employs a variable selection process, to refine the set of explanatory variables to be included in the regression models. After completing the variable selection process, we fit several linear regressions concerning the different flood types in order to assess the potential for significant differences in the loss-generating process. Taken together, the variable selection process narrows our focus to the most important variables, and the linear regression helps to establish their relative power in explaining the loss ratio across different flood types. From this information, we can draw inferences on the suitability of adapting flood loss modeling to a specific or a combination of flood types present in a flooding event.

2.2.1. Univariate Assessments (Stage 1)

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

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

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

2.2.2. Multivariable Regression (Stage 2)

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

2.2.2.1. Data Preparation

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

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

Additionally, in order to further increase data comparability, we focus only on the data points which are most likely to have similar loss-generating processes. Therefore, we focus only on respondents whose loss ratio was in the interval (0, 1). The rationale for this is that observations outside of this range (zero or total loss) present extreme outcomes and therefore a different set of responses to the predictor variables is likely. These cases would require additional steps, for example, including an additional probability model as in Rözer et al. (2019). We truncate the sample to include only the nonextreme cases as a methodological simplification for an otherwise minor but significantly different subsample. This truncation resulted in 2,268 observations for the building loss ratio. The univariate analyses provided the initial input into this selection, which resulted in "building value" being excluded from the analysis given that it is highly collinear with the building area.

2.2.2.2. Variable Selection

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

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

Our iterative process was based on 1,000 resampling runs per cycle. In the first cycle, all variables were included. Then, in each of the 1,000 resamples, variables were eliminated based on the stepwise elimination process employed (based on achieving the best AIC). In each of the 1,000 runs, the final set of selected variables was recorded. Then, the least selected variable was excluded from the analysis, after which a new cycle of 1,000 runs was conducted with the remaining variables. The process was repeated until all predictors were selected at least 400 times (i.e., 40% of samples) in the same 1,000-run cycle. The threshold of 40% was selected after preliminary rounds showed inconsistency among selected variables at lower rates. This approach was adopted because of the higher statistical capability of a larger data set, and the variable selection focused the analysis on fewer variables and hence fewer potentially missing variables per observation.

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

3. Results and Discussions

3.1. Univariate Assessments

3.1.1. Similarity of Flood Types' Subsamples

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

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

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

The variables related to preparedness show mixed differences across groups. For both variables, the emergency measures score and the awareness of living in a flood-prone area; there are two similar groups: levee breaches and riverine floods, on the one hand, and surface water floods and groundwater floods, on the other hand. Those affected by riverine floods had more recent experiences and also implemented more precautionary measures. The difference in experiences with other flood types, however, did not translate into a statistical difference in terms of our indicator for implemented precautionary measures. There is a higher share of insured households among those affected by levee breaches or riverine floods compared to those affected by surface or groundwater floods. This is an important difference to consider, because property-level adaptation is known to be effective at limiting flood losses, while insurance coverage alone is not (e.g., Hudson et al., 2014; Poussin et al., 2015).

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

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

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

Table 3
Central Values of Each Variable per Flood Type Grouped by Similarity After Post Hoc Tests With a Significance of 0.05 (Central Value Is the Average of Numeric Variables, the Mode of Nominal Variables)

Variable	Unit or range	Levee breach (n = 810)		Riverine (n = 2,509)		Surface water (n = 447)		Groundwater (n = 652)		Number of different groups
Hazard Characteristics										
Water Depth	[cm]	107	a	51	b	58	b	−66	c	3
Duration	[h]	283	a	122	b	64	c	146	b	3
Velocity	[0–6]	2.9	a	2.9	a	3.6	c	2.2	b	3
Contamination	[0–2]	0.81	a	0.49	b	0.59	d	0.24	c	4
Warning										
Warning Lead Time	[h]	42	a	22	b	9	c	25	b	3
Quality of Warning	[1–6]	3.53	a	2.82	b, c	3.21	c	2.59	b	3
Warning Information	[0–16]	3.42	a	2.64	b	1.31	d	2	c	4
Warning Source	5 classes [a,e]	Off+Ev (38%)	a	Off (29%)	b	No (37%)	d	Off (29%)	c	4
Gap Warning Action	[h]	18	a	5.4	b	3.74	b	8.11	a, b	2
Preparedness										
Emergency Measures	[0–17]	5.35	a	5.64	a	4.61	b	4.85	a, b	2
Precautionary Measures	[0–2]	0.59	a	0.78	b	0.58	a	0.68	a	2
Perceived Efficiency of Precautionary Measures	[1–6]	3.16	a	2.77	b	2.63	b	2.65	b	2
Flood Experience	[0–4]	0.55	a	1.11	b	0.77	c	0.86	c	3
Awareness of Flood Risk	% of y	70%	a	72%	a	58%	b	64%	b	2
Insurance cover	% of y	50%	a	47%	a	40%	b	40%	b	2
Building Characteristics										
Ownership	3 classes [a,b]	bO (83%)	a	bO (70%)	b	bO (74%)	b	bO (69%)	b	2
Build. Type	3 classes [a,c]	EFH (62%)	a	EFH (48%)	b	EFH (45%)	b	EFH (49%)	b	2
No. of Flats	[1–40]	1.7	a	2.54	b	2.27	b	2.59	b	2
Build. Quality	[1–6]	2.19	a	2.30	b	2.24	a, b	2.41	c	3
Build. Value	[1,000 €]	489	a	592	b	548	b	565	b	2
House/Flat area	[m^2]	125	a	113	b	115	a, b	117	b	2
Building area	[m^2]	185	a	246	b	216	b	268	b	2
Cellar	% of year	78%	a	82%	a	81%	a	93%	b	2
Household and Socioeconomic Features										
Age	[y]	55.7	a	56.4	a	54	a, b	53.1	b	2
Household Size	[n]	2.67		2.63		2.72		2.74		1
Children	[n]	0.24	a	0.30	a	0.34	a, b	0.40	b	2
Elderly	[n]	0.54		0.51		0.52		0.43		1
Income Class	[11–16]	14		14.1		14		14.2		1
Socioeconomic Status	[1–4]	2.94	a	2.72	b	2.73	b	2.63	b	2
Others										
Region	3 classes [a,d]	East (78%)	a	East (68%)	b	East (53%)	d	East (63%)	c	3
Event Year	6 years	2013 (49%)	a	2013 (38%)	b	2002 (58%)	d	2002 (50%)	c	3
Monetary Loss										
Building Loss Ratio	[%]	18	a	9	b	10	b	3	c	3
Building Loss (2013 Values)	[1,000 €]	76	a	44	b	47	b	19	c	3

Note. (a–d) Notation of subsamples that are statistically similar to each other; same letters mean similar subsamples; two letters next to a central value means it is similar to both letters' groups (see text for reading example).
[a]For nominal variables, only the share of the most frequent class (mode) is shown. [b]bO: building owner. [c]EFH: detached houses. [d]See description of federal states' grouping at Table 2. [e]Off: official warning; +Ev: official warning with evacuation order; No: no warning.

3.1.2. Discussion of the Univariate Analyses

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

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

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

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

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

3.2. Regression Analyses (Stage 2)

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

3.2.1. Variable Selection

Table 4 shows the percentage of times that each variable was included in the last predictor set generated by each variable selection process. The resulting regression model includes all variables that were identified in at least two of the four processes employed. The different stepwise elimination processes generated different outcomes because the relationship among the (included) independent variables may be complex, masking, or confounding their relationship to the dependent variable, affecting the result of the selection. Therefore, selecting variables that occur twice across elimination methods limits a potential bias from these complex relationships.

We see that in both types of procedures, seven variables were selected in more than 80% of the runs, that is, water depth, building area, contamination, duration, precautionary measures, insurance coverage, and flood type (Table 4). As previous literature has indicated (Figueiredo et al., 2018; Kreibich & Thieken, 2008; Vogel et al., 2018) and our variable selection has reinforced, flood type is an important potential predictor from our data set of different loss outcomes. Therefore, flood type seems to be a practical piece of information to collect.

It is sometimes suggested (Hair et al., 2019) that more rather than fewer variables should be retained in a regression when explanation is the aim rather than prediction. Therefore, we selected not only the most prominent variables in our selection process from Table 4 but also those identified to be more relevant in previous studies that used nonlinear and nonparametric methods over the same or similar data set (Merz et al., 2013; Schröter et al., 2014; Vogel et al., 2018). From these studies, we singled out only those predictors that were selected more than once across their variable selection methods. Details on this selection procedure and the specific methods are available in the supporting information (Text S1 and Table S1). Nine variables were singled out in this procedure, seven of which agreed with the results of our variable selection process. The year of the event and the building quality were repeatedly included in the abovementioned literature as important variables. However, since the year of the event is less fit for transferability exercises, only the building quality was added to our 12 initially selected variables shown in Table 4.

In the first steps of the stepwise iteration process, we begin with 31 potential predictors and 316 complete data points. However, as variables are excluded, the number of complete data points increases. In the final selected 13 predictor variable set, there are more than 1,800 complete data points. Therefore, the initial stages may suffer from the problems identified by Hair et al. (2019) but become potentially less problematic as the sample size increases to over twice the ratio suggested by Hair et al. (2019). This does, however, create the potential limitation that the initial steps may be overly driven by sample-specific concerns.

3.2.2. Multiple Regression per Flood Type

With the now 13 selected variables, we fit a linear regression to the whole data set (1,812 complete set data points) and separately for each flood type subsample. The comparison among coefficients of different variables is more reasonable with standardized coefficients (Hair et al., 2019), where the distribution of data within the subsample is accounted for and the units are standardized (i.e., the unit is one standard deviation for continuous variables), as shown in Table 5 and Figure 2. The fitted unstandardized coefficients and statistical indicators are shown in Table S2 in the supporting information.

When separating the regression per flood type subsample, the variables' importance changes (extended tables for each regression are presented in the supporting information Tables S3 to S7). However, it is still evident that the selected predictors are important either for overall loss modeling, across flood types, or at least for one flood type-specific model (Table 5). We highlight that flood experience was one of the least selected variables (see Table 4) and building quality was added later (see 3.2.1), but they were termed significant for levee breach- and surface water flood-specific models, respectively (Table 5).

As noticeable in Table 5, the subsamples for surface water or groundwater flooding are smaller in terms of observations and, therefore, have lower statistical power. Therefore, their signal is generally less accurate, as visible in Figure 2. In Figure 2, we compare the relevance of each factor for the final loss ratio. The estimates beginning with "FT_" stand for the dummy variables created after each flood type for the overall model, where levee breach is the reference category (i.e., estimate equals 0, not shown).

With standardized variables (centered on the mean and with variation relative to the standard deviation), one can see that water depth is the most important factor overall, as has been reflected in flood loss modeling since at least the 1970s (Grigg & Helweg, 1975). In the regression of the whole sample, there is no overlap

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Table 4
Percentage of Variable Inclusion in Backward Elimination and Forward Selection (at Least 40% in 1,000 Runs), With Building Loss Ratio as the Dependent Variable

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

between the two most important factors, water depth and building area, but there are overlaps between other factors. For levee breaches, both the building area and the state of being insured stand as the second most important factors, although the latter has quite a "spread-out" estimate. This is followed by flood experience class and contamination (see Table 5 and Figure 2).

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

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

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

Table 5
Standardized Coefficients and Statistical Significance of Variables Included in the Linear Regression of the Complete Set or per Flood Type

Variable	All	Levee breach (1)	Riverine (2)	Surface water (3)	Ground water (4)
n of complete data points	1,812	368	976	217	251
Hazard Characteristics					
Water Depth	0.0499 ***	0.0650 ***	0.0452 ***	0.0414 ***	0.0323 ***
Duration[a]	0.0165 ***	0.0123.	0.0149 ***	0.0225 *	0.0071.
Velocity	0.0060 *	0.0081	0.0048	0.0109	−0.0007
Contamination	0.0188 ***	0.0265 ***	0.0127 ***	0.0371 ***	0.0019
Preparedness					
Emergency Measures	−0.0061 *	−0.0014	−0.0064.	−0.0099	−0.0019
Precautionary Measures	−0.0116 ***	0.0007	−0.0138 ***	−0.0164.	−0.0130 **
Perceived Efficiency of Precautionary Measures (Efficiency Pre.)	0.0065 *	0.0121.	0.0044	0.0095	0.0032
Flood Experience	−0.0052.	−0.0222 **	−0.0044	0.0111	−0.0005
Insurance Cover	0.0152 **	0.0372 **	0.0186 **	−0.0210	−0.0016
Building Characteristics					
Building Area[a]	−0.0287 ***	−0.0376 ***	−0.0274 ***	−0.0231 **	−0.0151 ***
Building Quality	−0.0066 **	−0.0044	−0.0051	−0.0175 *	−0.0052
(No) Cellar	0.0152 *	0.0195	0.0096	0.0293	0.0171

[a]Log-transformed variables for linear regression. ***$P < 0.001$. **$P < 0.01$. *$P < 0.05$; $P < 0.1$.

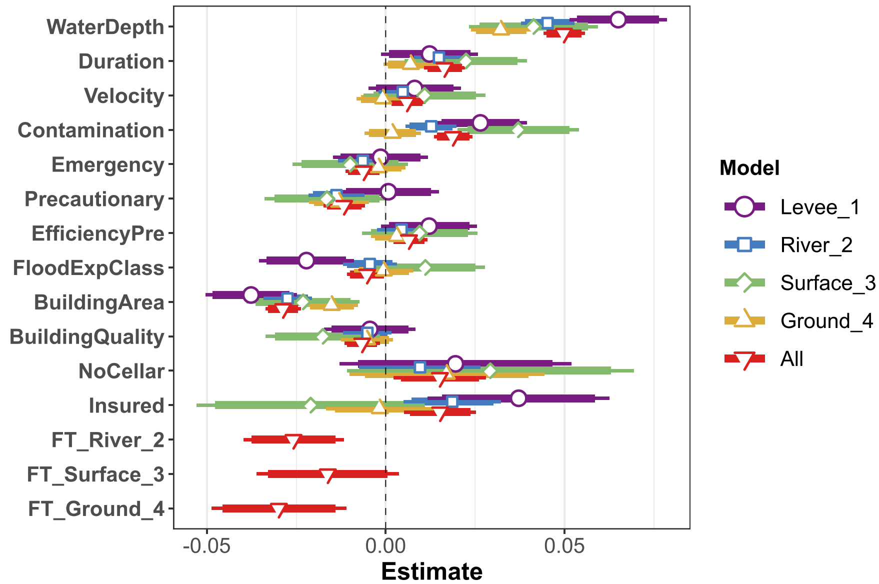

Figure 2. Standardized regression coefficients of the overall and flood type-specific models with 90% confidence interval thick bars. "FT_" stands for the dummy variables after flood types, where levee breach is the reference.

3.2.3. Discussion of the Regression Analyses

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

As hypothesized, flood type is a highly relevant predictor among the variables selected in more than 80% of random sampling runs for building loss ratio regressions (Table 4; see also Tables 5 and S2 and Figure 2). It is worth noting that besides hazard and building characteristics, features of preparedness were frequently selected, although these variables are rarely considered in flood loss models.

Variables related to flood warning were deemed of low relevance for the building loss ratio (Table 5), even though they were heterogeneous per flood type subsample (Table 3). This disagreement can be a result of mediated or interaction effects, that is, a variable's effect on the loss is influenced by another variable. For example, as mentioned by Kreibich, Müller, et al. (2017), the response is believed to be related to the warning lead time, by observing the responses from affected households and companies claiming that they would have acted (or done more) if they had been warned earlier. It should be acknowledged that flood warning has been considerably improved in Germany after 2002 (Kreibich, Müller, et al., 2017; Thieken, Kienzler, et al., 2016) and, thus, might lead to heterogeneous patterns in the data set. This issue of moderation or mediation effects could be dealt with, for example, through multilevel modeling. This advanced analysis, however, is outside the scope of this paper and shall be left to future research.

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

Since 2005, the Federal Water Act of Germany includes a paragraph stating that every person should take mitigating actions according to their own capacity (Thieken, Bessel, et al., 2016). Additionally, the Federal

Table 6
Comparison of Relevant Variables From Linear Regression of Markov-Blankets Developed per Flood Type

	Linear regression (significant coefficients)[b]					Markov-blanket (Vogel et al., 2018)[c]				
	All	Levee breach	Riverine	Surface water	Groundwater	All	Levee breach	Riverine	Surface water	Groundwater
Water Depth	1	1	1	1	1	X	X	X	X	X
Building Area[a]	2	2	2	3	2	X		X		
Contamination	4	4	6	2		X				
Precautionary Measures	8		5	6	3					X
Duration	5	6	4	4	4	X	X			
Insurance Cover	6	3	3							
Flood Experience	13	5					X			
Building Quality	9			5						
Perceived Efficiency of Precautionary Measures	10	7								
Emergency Measures	11		7							
Velocity	12									
Cellar	7					Not considered				
Event Year	Not selected					X		X		
Building Type	Not selected						X			
Income Class	Not selected								X	
Flood Type	3					X				

[a]Considered as building value in the work of Vogel et al. which was posed as collinear with building area, as explained in section 2. [b]The numbers show the order of the absolute mean of the coefficient estimate for a given linear regression. [c]"X" denotes inclusion of a variable in a given Markov-Blanket.

State of Bavaria recommends monitoring and maintenance of the fail-safe measures of oil tanks (LfU, 2014 apud Thieken, Bessel, et al., 2016), as this is an important source of contamination in floods which can also increase loss (Kreibich et al., 2011). Such actions show an escalating but still incomplete improvement of flood management in Germany, which reinforces the need to monitor such actions and consider them in flood loss estimations.

The most relevant study to compare ours to is the Markov-Blankets (MBs) approach from (Vogel et al., 2018), in which the authors compared different flood types. In general, our procedure signaled more variables as being relevant for loss-ratio modeling than in the respective MBs (see Table 6). Our results, however, display a degree of similarity with those from Vogel et al. (2018), except for the variables that were not considered in the study and one case, the presence of duration, which appears as an important predictor for levee breach MBs—but only of marginal significance in our linear regression selection. Comparing our work to that of Vogel et al. (2018), we reinforced in the previous section the potential order of importance of the influencing factors. In Table 6, we compared the more important variables of our selection procedure and the ones included in the MB from Vogel et al. (2018). The statistically significant predictors of our regressions are numbered according to the order of the coefficient estimates of the absolute mean, although their confidence intervals may overlap, as discussed above and shown in Figure 2. The ordering of variables is not possible using MBs.

It could be argued that the year of the event is not a helpful predictor of model transferability in a single-level regression framework but only as a nominal variable to help explain differences among the included events that the selected variables were not able to explain. Even though not selected for our potential predictor set, we compared our results with a model including the year of the event as dummy variable, but in fact, it was not considered as significant in our regression framework (see Table S2 in the supporting information).

Although causality cannot be tested, below we present interpretations of the reasons for differences in the significance and coefficients of predictor variables across flood type-specific models. Regarding flood experience, it is only significant for levee breach cases. This flood type being posed as the most destructive one (highest water depth, duration, and level of contamination; see Table 3), it may be argued that it requires a high level of preparedness for it to be effective and, as found in Lechowska (2018), a personal experience with flood influences awareness and preparedness more effectively than acquiring information from third parties (media or acquaintances). However, both emergency measures and precautionary measures were not deemed as significant for the levee breach-specific model, but the grading of the perceived efficiency of precautionary measures is slightly more significant than it is for other flood types. This indicates that there might be a confounding factor or a missing variable that explains this complexity.

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

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

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

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

4. Conclusions

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

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

While improved data collection for flood loss modeling or post event forensic analysis is a highly demanded task, it is a very resource-intensive one. Our findings indicate which information could be prioritized when collecting data to understand the impacts of a given flood type, which should help to steer data collection efforts toward reducing costs and fostering loss modeling. One example is that data gathering efforts should be broadened to systematically include emergency and precautionary measures. For instance, as can be seen in Table 6, we find that precautionary measures were important in four of the five model sets (as compared to 1 in Vogel et al. [2018]). Emergency behavior was also found to be important but to a lesser extent, highlighting the need to prepare for a flood over the longer term. Moreover, Figure 2 highlights how the impacts associated with these variables can differ significantly across flood types. Therefore, when combined with the wider literature investigating the effectiveness of precautionary behavior, we see that these variables should be included more often in loss modeling and risk analyses, as the actions of those at risk can change the effective level of risk faced and the resulting accuracy of risk assessments informed by risk models. Still in this domain, notwithstanding how the levels and features of early warning systems differ among the flood types, they were not included in the estimation model. This could be due to indirect influence that is not easily implemented in a single-level linear regression, indicating that further work should explore interactions between features/predictors. Moreover, it is possible that other predictors interact the same way that multicollinearity has been observed in at least one pair of variables (building value vs. building size), which may mask relevant effects in the loss ratio. This refinement must be further analyzed with different modeling and statistical methods.

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

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

Acknowledgments

This work received financial support from the DAAD (Graduate School Scholarship Programme, 2017-ID 57320205). Besides original resources from the partners, additional funds for data collection were provided by the German Ministry for Education and Research (BMBF) in the framework of the following research projects: DFNK 01SFR9969/5, MEDIS 0330688, and Flood 2013 13N13017. The surveys were conducted by a joint venture between the GeoForschungsZentrum Potsdam, the Deutsche Rückversicherung AG, Düsseldorf, and the University of Potsdam. The data sets of the 2005, 2006, 2010, 2011, and 2013 floods are available via the German flood loss database HOWAS21 (http://howas21.gfz-potsdam.de/howas21/).

References

Australian Institute for Disaster Resilience (2002). *Manual 27: Disaster loss assessment guidelines, CC BY-NC, Handbook Collection, 101 Pp*. Australia: Australian Institute for Disaster Resilience.

Beven, K. (2007). *Environmental modelling: An uncertain future?*. London: CRC Press.

Borcard, D., Gillet, F., & Legendre, P. (2018). *Numerical Ecology with R*, (p. 440). New York: Springer. https://doi.org/10.1007/978-3-319-71404-2

Bubeck, P., Botzen, W. J. W., & Aerts, J. C. J. H. (2012). A review of risk perceptions and other factors that influence flood mitigation behavior. *Risk analysis: an official publication of the Society for Risk Analysis*, *32*(9), 1481–1495. https://doi.org/10.1111/j.1539-6924.2011.01783.x

Cammerer, H., Thieken, A. H., & Lammel, J. (2013). Adaptability and transferability of flood loss functions in residential areas. *Natural Hazards and Earth System Sciences*, *13*(11), 3063–3081. https://doi.org/10.5194/nhess-13-3063-2013

Downton, M. W., & Pielke, R. A. Jr. (2005). How accurate are disaster loss data?: The case of U.S. Flood Damage. *Natural Hazards*, *35*(2), 211–228. https://doi.org/10.1007/s11069-004-4808-4

Einfalt, T., Hatzfeld, F., Wagner, A., Seltmann, J., Castro, D., & Frerichs, S. (2009). URBAS: Forecasting and management of flash floods in urban areas. *Urban Water Journal*, *6*(5), 369–374. https://doi.org/10.1080/15730620902934819

European Environment Agency (2019). *Economic losses from climate-related extremes in Europe*, (p. 29). Copenhagen, Denmark: EEA.

Falconer, R. H., Cobby, D., Smyth, P., Astle, G., Dent, J., & Golding, B. (2009). Pluvial flooding: New approaches in flood warning, mapping and risk management. *Journal of Flood Risk Management*, *2*(3), 198–208. https://doi.org/10.1111/j.1753-318X.2009.01034.x

Federal Emergency Management Agency (2013). *Hazus-MH flood technical manual*, (p. 569). Washington, D.C., USA: Mitigation Division.

Field, A., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. Los Angeles: Sage publications.

Figueiredo, R., Schröter, K., Weiss-Motz, A., Martina, M. L. V., & Kreibich, H. (2018). Multi-model ensembles for assessment of flood losses and associated uncertainty. *Natural Hazards and Earth System Sciences*, *18*(5), 1297–1314. https://doi.org/10.5194/nhess-18-1297-2018

Friendly, M. (2018). Heplots: Function boxM, R documentation, https://www.rdocumentation.org/packages/heplots/versions/1.3-5/topics/boxM.

Fuchs, S., Heiser, M., Schlögl, M., Zischg, A., Papathoma-Köhle, M., & Keiler, M. (2019). Short communication: A model to predict flood loss in mountain areas. *Environmental Modelling & Software*, *117*, 176–180. https://doi.org/10.1016/j.envsoft.2019.03.026

Fuchs, S., Keiler, M., Ortlepp, R., Schinke, R., & Papathoma-Köhle, M. (2019). Recent advances in vulnerability assessment for the built environment exposed to torrential hazards: Challenges and the way forward. *Journal of Hydrology*, *575*, 587–595. https://doi.org/10.1016/j.jhydrol.2019.05.067

Gerl, T., Kreibich, H., Franco, G., Marechal, D., & Schröter, K. (2016). A review of flood loss models as basis for harmonization and benchmarking. *PLoS ONE*, *11*(7), e0159791. https://doi.org/10.1371/journal.pone.0159791

Grigg, N. S., & Helweg, O. J. (1975). State-of-the-art of estimating flood damage in urban areas. *Journal of the American Water Resources Association*, *11*(2), 379–390. https://doi.org/10.1111/j.1752-1688.1975.tb00689.x

Gross, J., & Ligges, U. (2015). Nortest: Tests for normality.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis*. Andover, United Kingdom: Cengage Learning.

Handmer, J. (2003). The chimera of precision: Inherent uncertainties in disaster loss assessment. *Australian journal of emergency management, The*, *18*(2), 88.

Hasanzadeh Nafari, R., Ngo, T., & Lehman, W. (2016). Calibration and validation of FLFArs—A new flood loss function for Australian residential structures. *Natural Hazards and Earth System Sciences*, *16*(1), 15–27. https://doi.org/10.5194/nhess-16-15-2016

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis*, (2nd ed.). New York: Guilford Press.

Hrachowitz, M., Savenije, H. H. G., Blöschl, G., McDonnell, J. J., Sivapalan, M., Pomeroy, J. W., et al. (2013). A decade of predictions in Ungauged basins (PUB)—A review. *Hydrological Sciences Journal*, *58*(6), 1198–1255. https://doi.org/10.1080/02626667.2013.803183

Hristova, B. (2007). Analysis of the difference of flood damages caused by riverine flood, flash floods, levee breaches, and rising groundwater, Master Thesis, Faculty of Environmental Science and Process Engineering, Brandenburg Technical University Cottbus, Cottbus.

Hudson, P., Botzen, W. J. W., Kreibich, H., Bubeck, P., & Aerts, J. C. J. H. (2014). Evaluating the effectiveness of flood damage mitigation measures by the application of propensity score matching. *Natural Hazards and Earth System Sciences*, *14*(7), 1731–1747. https://doi.org/10.5194/nhess-14-1731-2014

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning*, (Vol. 103, p. 440). New York, NY: Springer New York.

Kelman, I., & Spence, R. (2004). An overview of flood actions on buildings. *Engineering Geology*, *73*(3–4), 297–309. https://doi.org/10.1016/j.enggeo.2004.01.010

Kienzler, S., Pech, I., Kreibich, H., Müller, M., & Thieken, A. H. (2015). After the extreme flood in 2002: Changes in preparedness, response and recovery of flood-affected residents in Germany between 2005 and 2011. *Natural Hazards and Earth System Sciences*, *15*(3), 505–526. https://doi.org/10.5194/nhess-15-505-2015

Korkmaz, S., Goksuluk, D., & Zararsiz, G. (2014). MVN: An R package for assessing multivariate normality. *The R Journal*, *6*(2), 151–162.

Kreibich, H., Christenberger, S., & Schwarze, R. (2011). Economic motivation of households to undertake private precautionary measures against floods. *Natural Hazards and Earth System Sciences*, *11*(2), 309–321. https://doi.org/10.5194/nhess-11-309-2011

Kreibich, H., & Dimitrova, B. (2010). Assessment of damages caused by different flood types. In D. de Wrachien, et al. (Eds.), *Flood Recovery, Innovation and Response II, WIT Transactions on Ecology and the Environment*, (pp. 3–11). UK: WIT PressSouthampton.

Kreibich, H., Müller, M., Schröter, K., & Thieken, A. H. (2017). New insights into flood warning reception and emergency response by affected parties. *Natural Hazards and Earth System Sciences*, *17*(12), 2075–2092. https://doi.org/10.5194/nhess-17-2075-2017

Kreibich, H., Petrow, T. H., Thieken, A. H., Müller, M., & Merz, B. (2005). Consequences of the extreme flood event of August 2002 in the city of Dresden, Germany. In D. Savic, & IAHS International Commission on Water Resources Systems (Eds.), *Sustainable Water Management Solutions for Large Cities*, *IAHS publication*, (pp. 164–173). Wallingford: IAHS.

Kreibich, H., Seifert, I., Merz, B., & Thieken, A. H. (2010). Development of FLEMOcs—A new model for the estimation of flood losses in the commercial sector. *Hydrological Sciences Journal*, *55*(8), 1302–1314. https://doi.org/10.1080/02626667.2010.529815

Kreibich, H., & Thieken, A. H. (2008). Assessment of damage caused by high groundwater inundation. *Water Resources Research*, *44*, W09409. https://doi.org/10.1029/2007WR006621

Kreibich, H., Thieken, A. H., Haubrock, S.-N., & Schröter, K. (2017), HOWAS21, The German flood damage database, Chap. 5, in *Flood damage survey and assessment: New insights from research and practice*, *Geophysical monograph*, vol. 228, D. Molinari et al., pp. 65–78, Wiley; American Geophysical Union, Hoboken, NJ, Washington, D. C

Lechowska, E. (2018). What determines flood risk perception? A review of factors of flood risk perception and relations between its basic elements. *Natural Hazards*, *94*(3), 1341–1366. https://doi.org/10.1007/s11069-018-3480-z
McCullagh, P., & Nelder, J. A. (1989). *Generalized linear models*, (Second ed.). London: Chapman & Hall/CRC Monographs on Statistics & Applied Probability, Taylor & Francis.
Merz, B., Kreibich, H., & Lall, U. (2013). Multi-variate flood damage assessment: A tree-based data-mining approach. *Natural Hazards and Earth System Sciences*, *13*(1), 53–64. https://doi.org/10.5194/nhess-13-53-2013
Merz, B., Kreibich, H., Schwarze, R., & Thieken, A. H. (2010). Review article "Assessment of economic flood damage". *Natural Hazards and Earth System Sciences*, *10*(8), 1697–1724. https://doi.org/10.5194/nhess-10-1697-2010
Merz, B., Kreibich, H., Thieken, A. H., & Schmidtke, R. (2004). Estimation uncertainty of direct monetary flood damage to buildings. *Natural Hazards and Earth System Sciences*, *4*(1), 153–163. https://doi.org/10.5194/nhess-4-153-2004
Meyer, V., Becker, N., Markantonis, V., Schwarze, R., van den Bergh, J. C. J. M., Bouwer, L. M., et al. (2013). Review article: Assessing the costs of natural hazards—State of the art and knowledge gaps. *Natural Hazards and Earth System Sciences*, *13*(5), 1351–1373. https://doi.org/10.5194/nhess-13-1351-2013
Molinari, D., Ballio, F., & Menoni, S. (Eds) (2017). *Flood damage survey and assessment: New insights from research and practice*, *Geophysical monograph*, (Vol. 228, p. 265). Hoboken, NJ, Washingston, D.C: Wiley; American Geophysical Union.
Molinari, D., de Bruijn, K. M., Castillo-Rodríguez, J. T., Aronica, G. T., & Bouwer, L. M. (2019). Validation of flood risk models: Current practice and possible improvements. *International Journal of Disaster Risk Reduction*, *33*, 441–448. https://doi.org/10.1016/j.ijdrr.2018.10.022
Murtaugh, P. A. (2014). In defense of P values. *Ecology*, *95*(3), 611–617. https://doi.org/10.1890/13-0590.1
Natho, S., & Thieken, A. H. (2018). Implementation and adaptation of a macro-scale method to assess and monitor direct economic losses caused by natural hazards. *International Journal of Disaster Risk Reduction*, *28*, 191–205. https://doi.org/10.1016/j.ijdrr.2018.03.008
Neubert, M., Naumann, T., Hennersdorf, J., & Nikolowski, J. (2016). The geographic information system-based flood damage simulation model HOWAD. *Journal of Flood Risk Management*, *9*(1), 36–49. https://doi.org/10.1111/jfr3.12109
Olesen, L., Löwe, R., & Arnbjerg-Nielsen, K. (2017). *Flood damage assessment: Literature review and recommended procedure*, (p. 44). Melbourne, Australia: Cooperative Research Centre for Water Sensitive Cities.
Osberghaus, D. (2017). The effect of flood experience on household mitigation—Evidence from longitudinal and insurance data. *Global Environmental Change*, *43*, 126–136. https://doi.org/10.1016/j.gloenvcha.2017.02.003
Parker, D. J., & Priest, S. J. (2012). The fallibility of flood warning chains: Can Europe's flood warnings be effective? *Water Resources Management*, *26*(10), 2927–2950. https://doi.org/10.1007/s11269-012-0057-6
Penning-Rowsell, E. C., Priest, S. J., Parker, D. J., Morris, J., Tunstall, S. M., Viavattene, C., et al. (2013). *Flood and coastal erosion risk management: A manual for economic appraisal, Xxiii*, (p. 420). Milton Park, Abingdon, Oxon: Routledge.
Pohlert, T. (2014). The Pairwise Multiple Comparison of Mean Ranks Package (PMCMR): R package.
Poussin, J. K., Wouter Botzen, W. J., & Aerts, J. C. J. H. (2015). Effectiveness of flood damage mitigation measures: Empirical evidence from French flood disasters. *Global Environmental Change*, *31*, 74–84. https://doi.org/10.1016/j.gloenvcha.2014.12.007
Rözer, V., Kreibich, H., Schröter, K., Müller, M., Sairam, N., Doss-Gollin, J., et al. (2019). Probabilistic models significantly reduce uncertainty in hurricane Harvey pluvial flood loss estimates. *Earth's Future*, *7*, 384–394. https://doi.org/10.1029/2018EF001074
Rözer, V., Müller, M., Bubeck, P., Kienzler, S., Thieken, A. H., Pech, I., et al. (2016). Coping with pluvial floods by private households. *Water*, *8*(7), 304. https://doi.org/10.3390/w8070304
Schröter, K., Kreibich, H., Vogel, K., Riggelsen, C., Scherbaum, F., & Merz, B. (2014). How useful are complex flood damage models? *Water Resources Research*, *50*, 3378–3395. https://doi.org/10.1002/2013WR014396
Seifert, I., Botzen, W. J. W., Kreibich, H., & Aerts, J. C. J. H. (2013). Influence of flood risk characteristics on flood insurance demand: A comparison between Germany and the Netherlands. *Natural Hazards and Earth System Sciences*, *13*(7), 1691–1705. https://doi.org/10.5194/nhess-13-1691-2013
Spekkers, M., Rözer, V., Thieken, A. H., ten Veldhuis, M.-C., & Kreibich, H. (2017). A comparative survey of the impacts of extreme rainfall in two international case studies. *Natural Hazards and Earth System Sciences*, *17*(8), 1337–1355. https://doi.org/10.5194/nhess-17-1337-2017
Stack Exchange (2014). Stepwise regression in R—Critical *p*-value, https://stats.stackexchange.com/q/97309.
Surminski, S., & Thieken, A. H. (2017). Promoting flood risk reduction: The role of insurance in Germany and England. *Earth's Future*, *5*, 979–1001. https://doi.org/10.1002/2017EF000587
Thieken, A. H., Bessel, T., Kienzler, S., Kreibich, H., Müller, M., Pisi, S., & Schröter, K. (2016). The flood of June 2013 in Germany: How much do we know about its impacts? *Natural Hazards and Earth System Sciences*, *16*(6), 1519–1540. https://doi.org/10.5194/nhess-16-1519-2016
Thieken, A. H., Kienzler, S., Kreibich, H., Kuhlicke, C., Kunz, M., Mühr, B., et al. (2016). Review of the flood risk management system in Germany after the major flood in 2013. *E&S*, *21*(2). https://doi.org/10.5751/ES-08547-210251
Thieken, A. H., Kreibich, H., Müller, M., & Lamond, J. (2017), Data collection for a better understanding of what causes flood damage—Experiences with telephone surveys, Chap 7, in *Flood damage Survey and Assessment: New Insights from Research and Practice*, *Geophysical Monograph*, vol. 228, D. Molinari et al. eds, pp. 95–106, Wiley; American Geophysical Union, Hoboken, NJ, Washingston, D. C.
Thieken, A. H., Kreibich, H., Müller, M., & Merz, B. (2007). Coping with floods: Preparedness, response and recovery of flood-affected residents in Germany in 2002. *Hydrological Sciences Journal*, *52*(5), 1016–1037. https://doi.org/10.1623/hysj.52.5.1016
Thieken, A. H., Müller, M., Kreibich, H., & Merz, B. (2005). Flood damage and influencing factors: New insights from the august 2002 flood in Germany. *Water Resources Research*, *41*, W12430. https://doi.org/10.1029/2005WR004177
Thieken, A. H., Olschewski, A., Kreibich, H., Kobsch, S., & Merz, B. (2008). Development and evaluation of FLEMOps—A new flood loss estimation model for the private sector. In D. Proverbs, et al. (Eds.), *Flood Recovery, Innovation and Response I*, (pp. 315–324). Southampton, UK: WIT Press.
Thieken, A. H., Petrow, T., Kreibich, H., & Merz, B. (2006). Insurability and mitigation of flood losses in private households in Germany. *Risk analysis: an official publication of the Society for Risk Analysis*, *26*(2), 383–395. https://doi.org/10.1111/j.1539-6924.2006.00741.x
Thieken, A. H., Seifert, I., & Merz, B. (Eds) (2010). *Hochwasserschäden: Erfassung, Abschätzung und Vermeidung*, (p. 300). München: Oekom-Verl.
Vogel, K., Riggelsen, C., Korup, O., & Scherbaum, F. (2014). Bayesian network learning for natural hazard analyses. *Natural Hazards and Earth System Sciences*, *14*(9), 2605–2626. https://doi.org/10.5194/nhess-14-2605-2014

10.1029/2019WR025943

Vogel, K., Weise, L., Schröter, K., & Thieken, A. H. (2018). Identifying driving factors in flood-damaging processes using graphical models. *Water Resources Research*, *26*, 8864–8889. https://doi.org/10.1029/2018WR022858

Vrieze, S. I. (2012). Model selection and psychological theory: A discussion of the differences between the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). *Psychological Methods*, *17*(2), 228–243. https://doi.org/10.1037/a0027127

Wagenaar, D., Lüdtke, S., Schröter, K., Bouwer, L. M., & Kreibich, H. (2018). Regional and temporal transferability of multivariable flood damage models. *Water Resources Research*, *54*, 3688–3703. https://doi.org/10.1029/2017WR022233

Zar, J. H. (2014). *Biostatistical Analysis* (5th ed.). Harlow: Pearson Education Limited.

Zeisler, P. R.-G., & Pflügner, W. P. (2019). *Arbeitshilfe zur Bewertung von Hochwasserschutzmaßnahmen in Baden-Württemberg*, (p. 138). Wiesbaden and Munich, Germany: Landes Baden-Württemberg.

Zeug, G., Weirather, M., Thieken, A., & Dillenhardt, L. (2019). *Untersuchung von Potentialen zur Nutzung von Copernicus-Daten und Diensten für die Umsetzung der Hochwasserrisikomanagementrichtlinie*, (p. 164). Dessau-Roßlau: Umweltbundesamt.

Zscheischler, J., Westra, S., van den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., et al. (2018). Future climate risk from compound events. *Nature Climate Change*, *8*(6), 469–477. https://doi.org/10.1038/s41558-018-0156-3