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Key Points:
- For the first time, a consistent approach for probabilistic flood loss modeling for residential buildings in Europe is presented
- The approach is validated for three case studies of varying spatial scale in Germany, Italy, and Austria
- BN-FLEMOps can be adapted to individual regions in Europe using an updating approach with empirical data from the target region

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A Consistent Approach for Probabilistic Residential Flood Loss Modeling in Europe

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Abstract In view of globally increasing flood losses, a significantly improved and more efficient flood risk management and adaptation policy are needed. One prerequisite is reliable risk assessments on the continental scale. Flood loss modeling and risk assessments for Europe are until now based on regional approaches using deterministic depth-damage functions. Uncertainties associated with the risk estimation are hardly known. To reduce these shortcomings, we present a novel, consistent approach for probabilistic flood loss modeling for Europe, based on the upscaling of the Bayesian Network Flood Loss Estimation MOdel for the private sector, BN-FLEMOps. The model is applied on the mesoscale in the whole of Europe and can be adapted to regional situations. BN-FLEMOps is validated in three case studies in Italy, Austria, and Germany. The officially reported loss figures of the past flood events are within the 95% quantile range of the probabilistic loss estimation, for all three case studies. In the Italian, Austrian, and German case studies, the median loss estimate shows an overestimation by 28% (2.1 million euro) and 305% (5.8 million euro) and an underestimation by 43% (104 million euro), respectively. In two of the three case studies, the performance of the model improved, when updated with empirical damage data from the area of interest. This approach represents a step forward in European wide flood risk modeling, since it delivers consistent flood loss estimates and inherently provides uncertainty information. Further validation and tests with respect to adapting the model to different European regions are recommended.

Plain Language Summary We present a novel, probabilistic approach to calculate flood losses for residential buildings in Europe. We show how the approach can be applied to the European scale and which data sets are required for the calculation. The validity of the approach is proven on the basis of three historic flood events in Italy, Austria, and Germany. This approach which delivers consistent flood loss estimates including uncertainty information supports more efficient flood risk management and adaptation policy in Europe.

1. Introduction

Floods are a global hazard with high socioeconomic impacts. In Europe, floods caused about 1,000 fatalities and 52 billion euro overall losses between 1998 and 2009 (EEA, 2010). The flood in central Europe in 2002 caused the largest economic losses with over 20 billion euro (EEA, 2010). Continuous effort is necessary to further reduce flood risks. The basis of efficient flood risk management is a reliable risk assessment on various spatial scales (de Moel et al., 2015; Merz et al., 2010). Continental flood risk analyses are important for the (re)insurance industry to assess accumulation risk and manage their risk portfolios, the financial sector to rate creditworthiness for investments (Kron, 2005), and for multinational companies to identify possible risks in their supply chains. Furthermore, European wide flood risk assessments are essential for governments to support climate change adaptation policies (Van Renssen, 2013) and to manage the European Union solidarity fund (Hochrainer et al., 2010). The European Flood Directive (EU, 2007) requests the European Union member states to provide risk management plans for areas with potentially significant flood risk. Decisions between alternative risk management options should be taken based on of flood risk analyses which are integrated with decision-support frameworks like cost-benefit analysis, multicriteria analysis, or robust decision making (Kunreuther et al., 2013). Risk analyses combine flood hazard modeling with loss modeling and provide quantitative estimates of expected flood losses in monetary terms.

Current flood loss assessments at European scale have shortcomings because they are based on heterogeneous, deterministic depth-damage functions for the individual countries (Jongman et al., 2014; Alfieri et al., 2015 , 2016; Dottori et al., 2017). Deterministic, depth-damage functions, which use only the water depth to estimate loss, are not able to adequately describe complex damage processes (Gerl et al., 2016; Meyer et al., 2013), so that associated uncertainties might be high but are unknown due to a lack of validation and missing uncertainty quantification. Differences in vulnerability between countries, for example, due to differences in building stock, are considered via different depth-damage functions, which leads to an inconsistent, fragmented loss assessment approach.

Depth-damage functions estimate the loss from the type or use of the element at risk (e.g., residential building) and the inundation depth (Smith, 1994; Wind et al., 1999). They are associated with high uncertainties, since flood damage processes depend on many more factors besides water-depth (Merz et al., 2004, Merz et al., 2013). Several studies identified additional loss determining variables like duration of inundation, sediment concentration, contamination of floodwater, flood experience, availability and content of flood warning, precautionary measures, and the quality of external response in a flood situation (e.g., Elmer et al., 2010; Hudson et al., 2014; Kreibich et al., 2009; Penning-Rowsell & Green, 2000; Smith, 1994; Thieken et al., 2005; Vogel et al., 2018). Particularly, resistance factors, such as the level of precautionary measures, are rarely taken into account by current loss models but are considered a precondition for the evaluation and development of effective risk mitigation strategies (Kreibich et al., 2015). Some multivariable models have been developed for example for Japan by Zhai et al. (2005), for the UK by Penning-Rowsell et al. (2005), and for Germany (Elmer et al., 2010; Kreibich et al., 2010). Studies have shown that the application of multivariable models that take several loss influencing factors into account are better able to describe complex damage processes and improve the reliability of flood loss modeling (Apel et al., 2009; Dottori et al., 2016; Merz et al., 2013). Loss modeling is subject to considerable uncertainty (de Moel & Aerts, 2011), which results from various sources including the incomplete knowledge and representation as well as the stochastic nature of the damage processes. It is, therefore, crucial to quantify uncertainties in flood loss estimates and hereby support reliable risk assessment as well as informed and robust decision making (de Brito & Evers, 2016; Pappenberger & Beven, 2006).

Recent studies developed ensemble approaches to provide uncertainty information for flood loss modeling (Figueiredo et al., 2018; Hasanzadeh Nafari et al., 2016; Wagenaar et al., 2017). Merz et al. (2013), Kreibich et al. (2017) and Schröter et al. (2018) demonstrated that tree-based model-ensembles, such as Bagging Decision Trees or Random Forests, are suitable for flood loss modeling on the microscale (e.g., individual buildings) and the mesoscale (e.g., land use units), as they are able to capture nonlinear and nonmonotonous dependencies between predictor and response variables and they take interactions between the predictors into account. Bayesian networks were used to develop probabilistic, multivariable flood loss models (Sairam et al., 2019; Schröter et al., 2014; Vogel et al., 2013; Wagenaar et al., 2018) for estimating flood loss of residential buildings on the microscale. Ensemble and probabilistic approaches inherently provide quantitative information on uncertainty associated with the variability of input data and model structure. Capturing and providing quantifications of the uncertainty in flood loss estimations is crucial for reliable risk assessment as well as informed and robust decision making (Pappenberger & Beven, 2006). Two main distinct approaches exist to develop flood loss models (Merz et al., 2010): empirical approaches which use loss data from flood events (e.g., HOWAS21 the German flood damage database; Kreibich, Thieken, et al., 2017) and synthetic approaches which use loss estimates or functions collected by building experts (e.g., the Multi Coloured Manual for the UK; Penning-Rowsell et al., 2005, and updated for 2010). Loss models can be based on empirical loss data surveyed on the one hand by science (e.g., Sairam et al., 2019; Schröter et al., 2014) and on the other hand by governmental agencies (e.g., Hasanzadeh Nafari et al., 2016; Merz et al., 2004) and insurance companies (e.g., Cortès et al., 2018; Spekkers et al., 2015) in the frameworks of loss compensation.

Spatial scales are an important aspect of loss modeling (Apel et al., 2009; de Moel et al., 2015). Microscale models calculate the loss for single objects, for example, residential buildings, while mesoscale models estimate loss for aggregated land use units. On continental scale, loss is usually modelled on the basis of land use units. Commonly a bottom-up approach is used for model development, which starts with a detailed analysis and modeling of losses to individual buildings (microscale) and develops an upscaling procedure for application based on land use units (Kreibich et al., 2010; Kreibich et al., 2016). That is, the structure of the microscale model is preserved, but for the input variables suitable proxy data, which are available area-wide, have to be acquired. For multivariable models, this is particularly challenging, since the use of proxies for the diverse input variables may introduce additional uncertainty (Kreibich, Botto, et al., 2017).

The lack of flood loss data and models in many regions requires the transfer of models to contexts for which they had not been developed. This is often done with insufficient justification and without reviewing the model suitability so that models usually show decreased predictive capability under these new circumstances (Cammerer et al., 2013; Schröter et al., 2014). This results in a patchwork of approaches with low comparability and consistency, also in respect to model validation (Jongman et al., 2012). Previous studies on continental and global flood loss estimation utilized deterministic, country-specific, stage damage curves and a more heterogeneous database (Alfieri et al., 2015; Huizinga, 2007; Huizinga et al., 2017). We propose an advanced approach for a consistent flood risk assessment on the continental scale and to overcome the current challenges (uncertainty quantification, spatial transferability, scale transfer), we suggest a probabilistic, multivariable model based on coherent data sources across Europe, which is adaptable to different regional situations, via model updating with local empirical data.

The objective of this study is to develop a consistent approach for probabilistic flood loss modeling for residential buildings in Europe, which is based on the upscaling of the microscale multivariable flood loss model **B**ayesian **N**etwork - **F**lood **L**oss **E**stimation **MO**del for the **p**rivate **s**ector (BN-FLEMOps) presented in Wagenaar et al. (2018). That is, the structure of the microscale BN-FLEMOps model is preserved, and European-wide proxy data are acquired and tested for the mesoscale application of the model. The approach is applied in the whole of Europe and validated using official loss figures of past flood events in three case study areas of varying spatial scale in Germany, Italy, and Austria. As a second objective, the possibility of adapting the loss model to different regions in Europe via updating the model with local empirical data is tested in the three case studies. The paper is structured in two parts. Section 2 contains the upscaling of the model BN-FLEMOps and the application of the approach in the whole of Europe. Section 3 contains the validation and adaptation test in the three case study areas. Both sections start with the descriptions of methods and data followed by the presentation and discussion of the results, respectively.

2. Consistent Approach for Flood Loss Modeling in Europe

We start this section with an introduction to the BN-FLEMOps which presents the basis and starting point of the European loss modeling approach (section 2.1). Next, the method and data for the upscaling of the model from microscale to mesoscale and the calculation of residential building loss on the mesoscale in Europe is explained (section 2.2). Section 2.3 contains the results and discussion of the model upscaling (section 2.3.1) and the application of the consistent approach for probabilistic flood loss modeling for residential buildings in Europe (section 2.3.2).

2.1. The Microscale BN-FLEMOps

The BN-FLEMOps (see Figure 1) has been developed for flood loss estimation on the level of individual residential buildings, that is, microscale applications, and was first presented by Wagenaar et al. (2018). It estimates relative building loss of residential buildings, that is, the relation between the absolute building loss and the replacement value of the building. Building loss includes all costs (e.g., costs of wages and material) that are associated with repairing the damage to the building structure caused by flooding. In this study, this model is further developed to be applicable on the mesoscale across Europe, preserving the structure of the Bayesian network (Figure 1) and using consistent proxy data sets. A Bayesian network is represented by a directed acyclic graph (DAG) which consists of nodes and arcs. The single variables in the network are represented by nodes and the direct dependencies between variables are represented by arcs between these nodes. The node at the tail of an arrow is called the parent node and the node at the head of an arrow is called the child node (Fenton & Neil, 2013; Lauritzen, 1996). As an example from the structure of BN-FLEMOps (Figure 1): The variable inundation duration (d) is the child node with the variable return period (rp) as the parent node. The relation between these two variables reads as duration (d) depends on return period (rp). Wagenaar et al. (2018) described the derivation of the Bayesian network structure using a combined data and expert-driven approach. The resulting DAG with a given direction of arcs does not necessarily present a causal relationship (Vogel et al., 2018). For the calculation of relative building loss (rbloss), it is irrelevant in which direction the arcs are pointing. Inference from the Bayesian network can be made in any

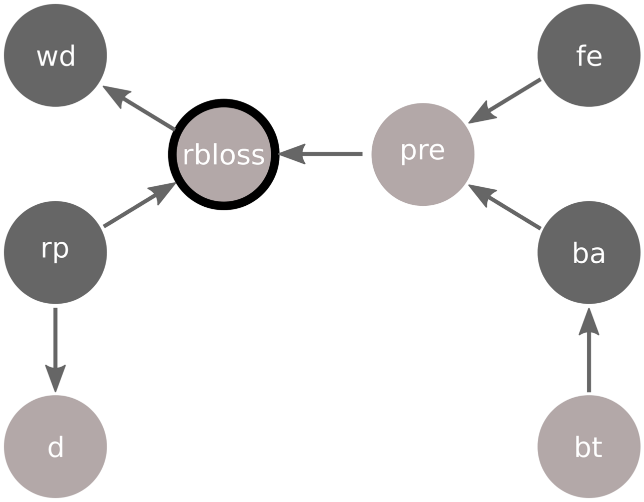

Figure 1. Model structure with the variables of BN-FLEMOps (adapted from Wagenaar et al., 2018) rbloss = relative building loss; wd = water depth; rp = return period; d = inundation duration; pre = precautionary measures; fe = flood experience; ba = footprint area of the building; bt = building type). The highlighted node "rbloss" indicates the target variable relative building loss. The dark gray nodes represent the variables available for mesoscale applications in Europe; see section 2.3.1.

direction and for any variable included. (Fenton & Neil, 2013). As the DAG represents the conditional (in)dependency structure of the variables this translates into a conditional probability for duration given the return period, formalized as P(d|rp), where P denotes the probability. Indirect dependencies between variables are shown by the sequence of arcs between nodes. The DAG represents the joint probability of all variables in the Bayesian network respecting these dependencies and independencies. The joint probability for the variables of the BN-FLEMOps nodes is given according to the DAG as equation ((1)

$$P\,(\mathrm{rbloss, bt, ba, fe, d, rp, wd, pre}) = P\,(\mathrm{fe})^*P\,(\mathrm{bt})^*P\,(\mathrm{rp})^*P\,(\mathrm{ba}|\mathrm{bt})^*P\,(\mathrm{d}|\mathrm{rp})^*P\,(\mathrm{rbloss}|\mathrm{rp, pre})^*P\,(\mathrm{wd}|\mathrm{rbloss})^*P\,(\mathrm{pre}|\mathrm{fe, ba}) \tag{1}$$

BN-FLEMOps uses discretized variables and the joint probability distributions are represented as conditional probability tables or node probability tables (NPT). These tables contain the conditional probabilities for each parent node and their associated child node(s). The underlying empirical microscale damage database contained information of damaged residential buildings, which were collected in surveys via computer-aided telephone interviews after the floods in 2002, 2005, 2006, 2010, 2011, and 2013 in Germany. A total of 1,522 data sets with complete observations of all model variables were available. The conditional probability tables of the Bayesian network were derived from these 1,522 data sets using maximum likelihood estimation. The variables were discretized on an equal frequency basis with water depth and relative building loss in 10 classes, return period and inundation duration in five classes and footprint area of the building in three classes (Table 1). The number of classes was set based on expert judgment and data availability, aiming at a compromise between a stable network, a detailed representation of variables and their presumed importance. The other variables, that is, building type, flood experience, and precautionary measures, are discrete by definition (Wagenaar et al., 2018). Figure 1 and equation (1) for the joint probability show that the occurrence of the variable of interest, relative building loss, is directly conditioned on the return period, and precautionary measures and that water depth is conditioned on relative building loss. The latter does not indicate a causal relationship since it is rather the other way around with higher water depth causing higher relative building losses. However, since the directions are not of interest for the calculation of relative building loss (Fenton & Neil, 2013), we kept the structure as reported in Wagenaar et al. (2018) derived from the data-driven approach. The variables

Table 1
Overview of the Variables of BN-FLEMOps

Abbreviation	Variable	Unit	Discrete classes	Variable type
rbloss	Relative building loss of residential buildings—relation between the absolute building loss and the replacement value of the building as at event year	Relative 0 to 1	10	Continuous
wd	Water depth relative to ground level	Meters	10	Continuous
rp	Return period—calculated for peak flood discharges in subcatchments with extreme value statistics on the basis of annual maximum series of discharge for gauges in the flood-affected areas (see Elmer et al., 2010)	Years	5	Continuous
d	Inundation duration at the affected building	Hours	5	Continuous
pre	Precautionary measures—indicator (no, good, very good precaution) considering the number and type of private precautionary measures undertaken	Score	3	Ordinal
fe	Flood experience—number of floods experienced before the respective damaging flood event	Score	6	Ordinal
ba	Footprint area of residential buildings	Square meter	3	Continuous
bt	Building type: 1 = single-family houses, 2 = (semi)detached houses, 3 = multifamily houses	Index	3	Nominal

water depth, return period, and precaution constitute the so-called Markov blanket of relative building loss. This is of special interest because the availability of observations for the variables within the Markov blanket of relative building loss makes it conditionally independent from all other variables in the DAG (Fenton & Neil, 2013; Murphy, 2012; Pearl, 1988). For example, computing the relative building loss for a given combination of water depth, return period, inundation duration and precautionary measures, the value of inundation duration is not of interest because having observations for the variable return period, relative building loss is conditionally independent of duration. Hence, if all variables of the Markov blanket of relative building loss are available, other variables are no longer considered in the estimation of rbloss. On the other hand, if data are missing for a node of the Markov blanket, the model can still be applied but the uncertainty of the model results will increase. Information about precautionary measures are missing for the mesoscale application of the model and is treated as an extra unknown variable (together with relative building loss); thus, the Bayesian network calculates a conditional probability for the missing variable precaution according to the NPTs conditioned on flood experience and building area.

2.2. Method and Data for Model Upscaling and Application at the Mesoscale in Europe

2.2.1. Input Data Available for the European Domain

In its original application at the microscale, all variables used to estimate the flood loss with BN-FLEMOps were derived from the empirical microscale damage database (Wagenaar et al., 2018). For the mesoscale application in Europe, such detailed information are not available. Instead, suitable proxy data sources have to be used (Figure 2). The compilation and preparation of proxy data focuses on the Markov-blanket variables of relative building loss and besides has to consider the availability of data sources. Hence, only those variables marked in dark gray in Figure 1 (wd, rp, fe and ba) are included in the mesoscale model. Accordingly, data sources are needed to quantify the flood intensity and the resistance characteristics of the buildings.

Flood impact intensity is described by water depth, return period, and inundation duration. These variables are commonly estimated by hydrodynamic models, which are either used to calculate flood inundation scenarios for various return periods or to model inundation areas of real flood events. For the application of our loss modeling approach on the European domain, we used the inundation scenario for a continent-wide flood with 100 years return period provided by the Joint Research Center (Alfieri et al., 2014). The Joint Research Center pan-European flood maps were computed using a model chain that includes hydrological modeling, derivation of flood hydrographs, and hydrodynamic modeling. The maps have a 100 m resolution of water-depth and cover catchments with areas larger than 500 km^2. Flood protection infrastructure such as dikes, embankments or floodwalls, etc. are not considered in this hazard scenario.

The presence of precautionary measures is very heterogeneous within and across regions, and to our knowledge no database or register of these measures exists for Europe. For this reason, the parent nodes flood experience and building area are used to infer the state (or class) of precautionary measures within the Bayesian network model.

The variables building area and flood experience describe the resistance characteristics of the residential buildings. OpenStreetMap (OSM contributors, 2018a) was identified as a suitable source to provide information on the building footprint area. OSM is a geographic database with worldwide coverage. It relies on a community of contributors to constantly add information and assure regular updates to enhance accuracy and completeness. The OSM project provides freely available open data and is nowadays considered a reliable source for most civil and common use cases (Barrington-Leigh & Millard-Ball, 2017). To obtain the building footprint area of residential buildings the database was filtered to exclude objects with nonresidential usage.

In previous studies (Merz et al., 2013; Schröter et al., 2014; Thieken et al., 2005), flood experience is used as an indicator which is based on different factors such as the number of experienced floods, the associated losses with the latest flood experienced and the time period since the last flood event. These details are available from the empirical microscale damage database and are not available on the same level of detail in Europe. Thus, the proxy data for the variable flood experience had to be simplified for the mesoscale application. Based on the assumption that the more floods individuals have experienced during the last years, the greater is their flood experience, the mesoscale variable for fe is represented by the number of floods that occurred during the last 25 years in the particular region. To derive the number of floods people were exposed to at their home location, we use the database of the Dartmouth Flood Observatory (DFO) (Brakenridge,

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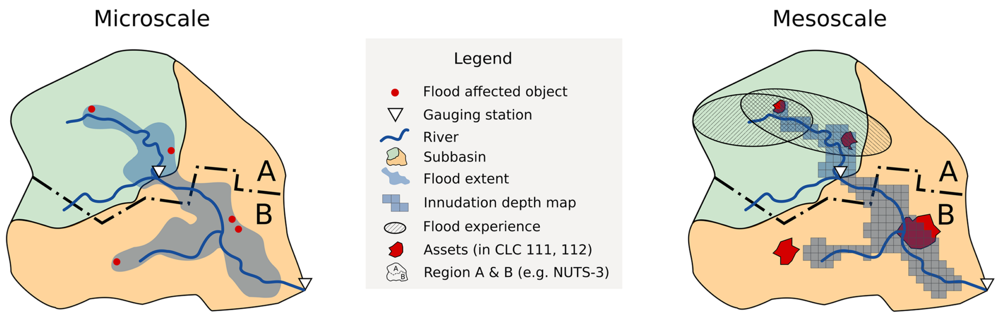

Predictor variable	Data source	Data description
Return period (rp)		- Return period per object - Value from representative gauging station allocated to affected objects
Duration (d)	Interview	- Duration (days/hours) per object
Water depth (wd)	Interview	- Water depth per object
Building area (ba)	Interview	- Building area per object
Flood experience (fe)	Interview	- Flood experience per object index based on number (severity) of recent floods

Predictor variable	Data source	Data description
Return period (rp)	Real event Syntetic event set	- Return period per subbasin - Scenario value from reprsentative gauging station for real or syntetic events
Duration (d)	Hydraulic model	- Duration per pixel - Value from hydraulic model output
Water depth (wd)	Hydraulic model	- Water depth per pixel - Value from hydraulic model output
Building area (ba)	OSM	- Building area per response unit - Distribution per region based on OSM footprint areas
Flood experience (fe)	DFO	- Flood experience per response unit - Value from DFO historical

Figure 2. Comparison between the variables and data source for the microscale and mesoscale application of BN-FLEMOps.

2018). The DFO catalog is an archive of historic flood events starting in the year 1985. This archive comprises maps of flood-affected areas with a set of additional characteristics like severity, start and end date, and the cause for flooding. One drawback of this data source is that the spatial extent of flood-affected areas is very coarse, as it often consists of an outline of the affected area instead of a detailed flood footprint. Nevertheless, to our knowledge, this data set is the only one that provides a comprehensive record of flood events in space and time across Europe. With these European wide data sets for the variables water depth, return period, building area and flood experience, relative building loss can be estimated for residential buildings using the BN-FLEMO model. To further obtain absolute building losses, replacement cost values of residential buildings are needed.

The monetary values of the exposed residential buildings are taken from a European asset map developed for this study. This asset map was created by adapting the approach by Huizinga et al. (2017) who found a relationship between construction cost (material and labour cost) and gross domestic product (GDP) per capita by comparing national socioeconomic parameters with construction cost surveys from multinational construction companies. The replacement values of buildings for the European asset map are calculated using the relation of construction cost and GDP per capita on the NUTS-3 level to account for regional differences. To develop the European asset map for this study we used the GDP per capita information for all NUTS-3 regions available from Eurostat (2018) for the year 2013. The GDP per capita values can be adjusted to different flood event years by the GDP per capita growth rate of the respective region affected such as a subbasin or municipality. The resulting asset values for residential buildings reflect tangible monetary assets and are based on the concept of reconstruction cost. The reconstruction costs of residential buildings are translated to unit area values in (euro/m^2) for NUTS-3 regions by disaggregation on the CORINE Land Cover (CLC) 2012 (EEA, 2016) classes: *continuous urban fabric* (111) and *discontinuous urban fabric* (112) using asymmetric mapping following Huizinga et al. (2017). The European asset map created by this approach contains distinct unit area values (euro/m^2) for residential buildings in NUTS-3 regions and is available for all European countries covered by CLC data.

2.2.2. Mesoscale Loss Calculation

Loss estimation includes three steps: (i) data preprocessing, (ii) computation of relative loss estimates, and (iii) the conversion to monetary values.

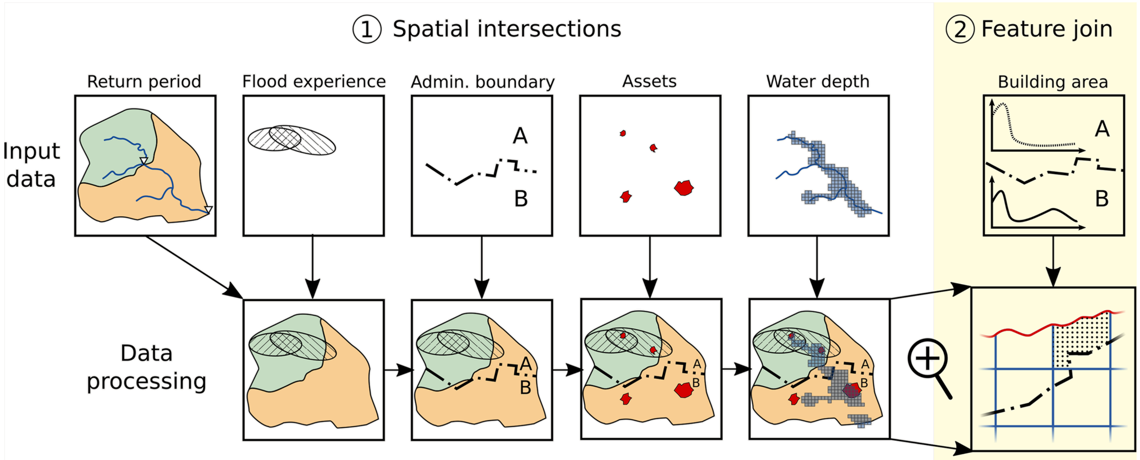

Figure 3. Flow chart of the input data preparation for the mesoscale loss calculation in BN-FLEMOps. 1 = spatial intersections: Shows the stepwise process of the spatial intersection of model input data. In subsequent processing steps, the data sets are overlaid and intersected to combine their information in one data layer. The response units are the areas created by the intersection and within these areas; all variable values are constant. 2 = feature join: Displays the magnified response units and the join of building area values based on administrative boundaries.

Data Preprocessing and Spatial Intersection. Data preprocessing is a two-step procedure consisting of the spatial intersection of data sets and joining features to resulting spatial units. Figure 3 illustrates the individual steps in a flow chart of input data preparation. First, the watershed subbasins holding the return period value (rp), the DFO data set providing the value for flood experience (fe), the administrative boundaries (required for the second step), the CLC classes holding the unit area values (assets) and the polygonized water depth raster providing the water depth values (wd) are spatially intersected, see second row of Figure 3. In the intersection process, the data sets are handled as polygons to ensure that no spatial details are lost—that means that even cells of the water depth raster might be subdivided by one or more other input data sets (see Figure 3). The result of the intersection is a set of response units which are spatial polygons holding single values for water depth, return period, flood experience as input variables for the BN-FLEMOps model and in addition the unit area value of residential buildings. The code of the administrative regions is not directly used as a model input but is required for joining features to the response unit within the second step of the data preprocessing. Based on the OSM data set, a distribution of building footprint area is available for each administrative region (NUTS-3). For each response unit, we sample one value of building area from the distribution of the corresponding NUTS-3 region. A response unit is exemplarily shown on the bottom right of Figure 3 as the dotted polygon area. In this example, the cells of the water mask (blue lines) are only separated by the administrative boundary (black dashed line) and the asset map (red line) and hold the same values for the other variables (rp, fe). As a result, each response unit holds the values for the input variables of the BN-FLEMOps model to estimate relative building loss per response unit.

Computation of Relative Loss Estimates. Applying BN-FLEMOps means inferring from the Bayesian network following the joint probability distribution (equation (1)). The joint probability distribution is depicted by the NPTs which were generated following the dependency structure of the Bayesian network and the empirical loss data. The conditional probability distribution of our target variable "brloss" can therefore be queried from the NPTs given the available input variables. The application of the Bayesian network results in a probability distribution of relative building loss for each response unit. Summary statistics are reported as model results. The book "Bayesian networks—With examples in R" by Scutari and Denis (2014) provides a comprehensive introduction to the application of discrete Bayesian networks.

Conversion to Monetary Values. The final processing step is the calculation of the absolute monetary loss by multiplying the distribution of loss ratios with the unit area value for each response unit and the surface area of the response unit. The result is a distribution of absolute loss in euro per response unit. Absolute monetary loss values for response units can be spatially aggregated, for instance within their respective NUTS-3 regions or river basins.

2.3. Results and Discussion of Model Upscaling and Application at European Scale

2.3.1. Model Upscaling—Suitability Test of Proxy Variables

To assess the suitability of this proxy data source, we compare the distribution of building footprint areas from OSM and the empirical microscale damage data (msdd) in 25 German NUTS-3 regions where 30 or more observations are available to have a reasonable number of data points for comparison. Buildings larger than 500 m^2 were excluded from the building data set, to avoid not correctly confined buildings (block of houses not separated into the individual buildings) and wrongly assigned objects (like large scale industry buildings). The threshold to exclude buildings lager than 500 m^2 from the OSM data set was derived by comparison with the empirical msdd database.

The median building footprint area in the empirical microscale damage database aggregated for the 25 NUTS-3 regions is 154 m^2 in comparison to 136 m^2 in the OSM geometries. This divergence of building areas between the empirical microscale damage data and the proxy data from OSM is also present at a disaggregated NUTS-3 level. Figure 4 compares the distribution of building area values from both data sources in 25 NUTS-3 regions in Germany. The OSM data set often displays slightly lower mean values and narrower interquartile ranges. The building area distributions of the empirical microscale damage data differ considerably more between the individual NUTS-3 regions in comparison to the more homogeneous building area distributions of the OSM data. Even though these differences between empirical microscale damage data and mesoscale proxy data from OSM exist, OSM seems to provide suitable information about the variable building area for the application of BN-FLEMOps on the mesoscale. Besides, it is currently the best pan-European data set available to describe building footprint area, and it is continuously improved by mapping efforts of OSM contributors and the integration of existing data sets. The distribution of the footprint area of residential buildings in the NUTS-3 region in Europe is sampled to populate the building area variable in each responds unit. Higher median building areas in peripheral regions like the west coast of Norway may partly be attributed to low mapping coverage. Prominent landmark buildings are more likely to be mapped first and are therefore dominant in regions with low mapping completeness. This may result in a higher median building area compared to other European regions. France and the Netherlands, on the contrary, have a very complete building map since official data sets such as cadastral data provided by Direction Générale des Impôts and data from AND (www.and.com) were integrated into the OSM database (Mooney & Minghini, 2017; OSM contributors, 2018b). This more consistent representation of individual buildings may have contributed to the relatively low mean building areas in France and the Netherlands. The building area variable in the mesoscale application of BN-FLEMOps is sampled from the distribution of building footprint areas per NUTS-3 region, while the median value is solely used to present the European data set on the map.

European wide proxy data of the variable flood experience for the mesoscale application of BN-FLEMOps is derived from the DFO catalog. To test the suitability of this proxy data to capture the state of flood experience and its variation across regions, we compare the number of floods experienced during the last 25 years as reported in the empirical microscale damage data to the flood occurrences according to the DFO catalog per NUTS-3 region. Assuming a minimum threshold of 30 or more empirical data points per NUTS-3 region, we compared the aggregated data in 37 NUTS-3 regions in Germany (Figure 5). The threshold of 30 empirical data points is a compromise between the availability of a sufficiently large number of observations in a NUTS-3 region, and a sufficiently large number of NUTS-3 regions so that comparisons are meaningful. Most people have reported that they had been affected once or twice by floods before the event they were asked about in the telephone surveys (Figure 5). The DFO archive counts two to three floods in the same areas on average. The reason for this mismatch may be the coarse spatial resolution of the DFO data, which contains a significantly larger area than what was impacted by the flood. To avoid an overestimation of flood experience in the mesoscale application of BN-FLEMOps this offset between both data sets is corrected by introducing a bias correction factor of minus one which improves the agreement of the histograms of both data sets (Figure 5). Figure 6 shows the spatial footprints of all large historic floods registered in the DFO catalog that occurred in Europe in the time span from 1985 to 2015. In the model, the number of historic floods is counted for each response unit and is used on the mesoscale to describe flood experience in the model.

The European asset map (Figure 7) displays regional differences in unit area values of residential buildings giving the reconstruction costs. Metropolitan areas such as London, Paris, Madrid, Rome, and Berlin are associated with higher unit values than their surrounding areas. Scandinavian countries, Switzerland and

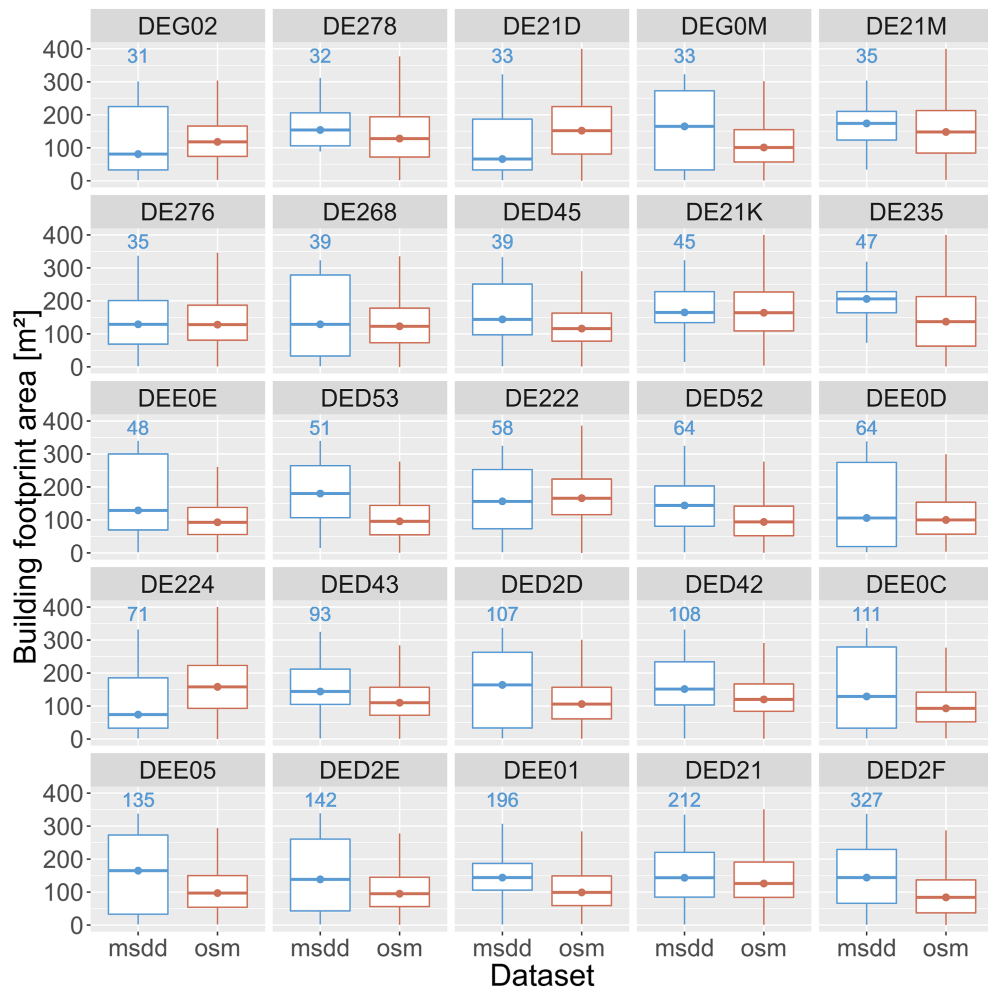

Figure 4. Comparison of box plots of building area distributions (*y* axis) forming empirical microscale damage data (msdd) and mesoscale proxy data derived from OSM data (*x* axis) in 25 NUTS-3 regions in Germany (panels). The number of empirical data points in the respective NUTS-3 region is given in blue.

the Benelux-countries show overall high unit values of residential buildings, while eastern and south-eastern European countries display lower unit area values of residential buildings. To use the asset map for the calculation of absolute losses on the mesoscale, the building values need to be translated to the respective year of the analyses. This is done via the relation between construction cost and GDP per capita developed by Huizinga et al. (2017) on construction cost data from 2010 and 2013. Uncertainties associated with this translation of values might be higher for earlier or later years than from 2010 to 2013, as then the GDP per capita might not have the same correlation with the construction cost as was found for this time period. The spatial resolution of the European asset map is determined by the accuracy and minimum mapping distance of the CLC data set. Individual buildings in predominantly rural areas are not always represented, and thus are not accounted for in the loss estimates.

2.3.2. Flood Loss Assessment at European Scale

The results of the loss estimation for the 100-year European flood map are shown in Figure 8 in terms of the median, the 20% quantile (Q_{20}) and the 80% quantile (Q_{80}) loss based on the distribution of absolute monetary losses per NUTS-3 region across Europe. For this flood scenario, the highest flood losses are expected in the flood plains of major European rivers, such as Rhine and Meuse, Danube, Seine, Loire, and Po. Note that the flood scenario does not account for any flood protection infrastructure in place. NUTS-3 regions in the Netherlands, France Austria, Hungary, the Czech Republic, and Belgium would be most affected by a 100 years flood scenario. Groot-Rijnmond (NL339) in the Netherlands would suffer the overall highest losses with 2.6 billion euro (Q_{20} = 1.1; Q_{80} = 7.7) loss to all residential buildings in the region. Figure 8 depicts

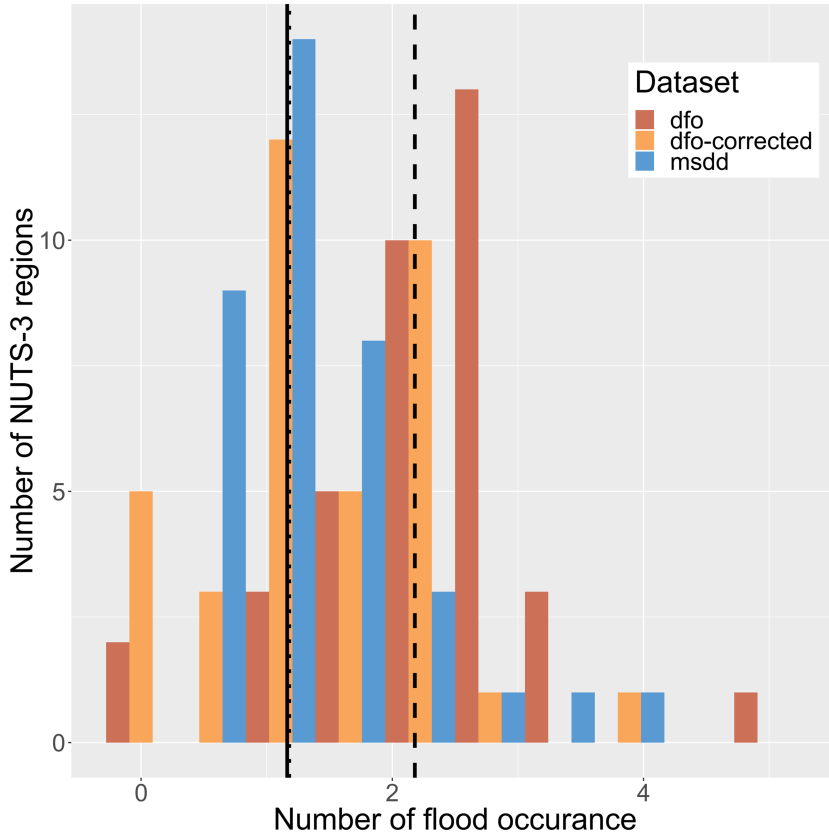

Figure 5. Histogram of the mean values of the number of floods that have occurred according to the empirical microscale damage data (msdd), mesoscale proxy data derived from dfo in 37 German NUTS-3 regions, and dfo data with bias correction factor minus 1. The black lines indicate the overall mean of the data sets (dfo = dashed; dfo-corrected = dotted; msdd = solid).

the accumulated flood loss for residential buildings in NUTS-3 regions in Europe. Therefore, large NUTS regions such as in Sweden tend to show high accumulated losses, whereas smaller regions in Germany have lower accumulated losses. On a national level Germany and France are estimated to have the highest losses with 14.5 billion euro (Q_{20} = 5.8; Q_{80} = 38.9) and 13.2 billion euro (Q20 = 5.4; Q80 = 36.1) respectively. A data set of the flood loss distribution per NUTS-3 region in 10% quantile steps and a detailed description is published in (Lüdtke et al., 2017). The total accumulated loss for residential buildings in Europe is estimated to 79.0 billion euro (Q_{20} = 32.3; Q_{80} = 213.8) for the continent-wide 100 years flood hazard map. A comparison with the aggregated direct flood losses estimated for 45 land use classes in European countries by Alfieri et al. (2015) showed that the losses estimated by BN-FLEMOps were lower for most countries. This is a plausible result since BN-FLEMOps only considers residential buildings in the CORINE land use classes for urban fabric.

3. Model Validation and Adaptation Test in Three Case Study Areas

Section 3.1 presents the three case studies including the available data with respect to the inundation area, validation data and data for the adaptation test. Section 3.2 describes the method for updating the loss model to adapt it to local settings. The following sections present the results and discussion of the validation of the general BN-FLEMOps model (section 3.3), and the result of the adaptation test, that is, application of the loss model with two update steps in the three case study areas (section 3.4).

3.1. Case Study Descriptions

The BN-FLEMOps model is validated on the mesoscale in three different case studies. We use the European proxy data for building area and flood experience as inputs to the model. Flood intensity information

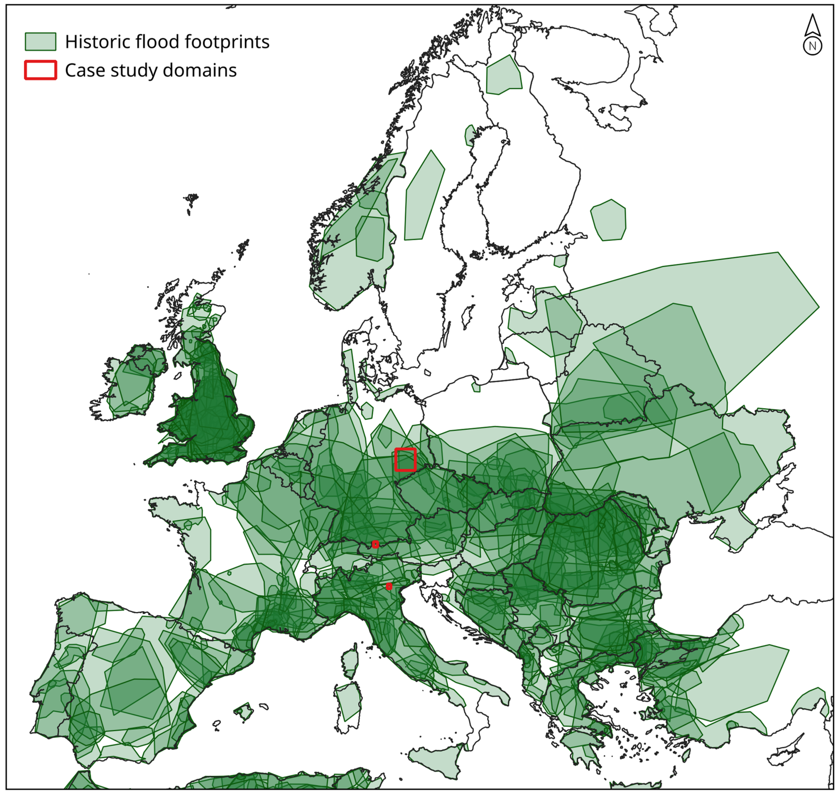

Figure 6. European map of historic flood events from the DFO catalog for the period of 1985 to 2015. The red squares indicate the case study areas in Germany, Austria, and Italy.

including water depth and return period are available from local data sets. Loss estimates are compared with official loss figures from past flood events.

3.1.1. Case Study Caldogno, Italy

The Veneto Region (Italy) was affected by persistent rain between 31 October and 2 November 2010, particularly in pre-Alpine and foothill areas. In some locations, accumulated rainfall exceeded 500 mm in 72 hr, one of the most intense events of the last 50 years (Regione del Veneto, 2011a). Various rivers overflowed, flooding an area of around 140 km^2 causing three fatalities, and 3,500 evacuees. Flood losses among residential, commercial and public assets amounted to a total of 426 million euro. In Caldogno, a municipality in the province of Vicenza, losses to those sectors reached 25.7 million euro (Regione del Veneto, 2011b).

Official Loss Figure for Validation. Losses to residential buildings amounted to 7.55 million euro in the city of Caldogno, which is used for validation in this study. This official loss figure is provided by the municipality of Caldogno and corresponds to restoration costs that were collected and verified in the scope of the loss compensation process after the event (Scorzini & Frank, 2017).

Flood Map. Water depth and flow velocity maps were estimated using a coupled 1-D/2-D model of the area between the municipalities of Caldogno and Vicenza. These flood intensity metrics were originally computed on a 5 m × 5 m spatial grid (Figueiredo et al., 2018; Scorzini & Frank, 2017) and have here been resampled to 10 m × 10 m.

Empirical Microscale Loss Data for Model Updating. For 295 damaged residential buildings, building characteristics at the microscale were obtained through surveys. These characteristics include building type, structural type, number of floors, quality, and year of construction. Building areas were derived from the region of Veneto's cadastral map, and building values were estimated from data provided by the Chamber of Commerce of Vicenza (Figueiredo et al., 2018). Data about the inundation duration and water depth at the building were taken from the flood map described above. Thus, in this case study, the flood intensity information used for model updating is the same as for the model application.

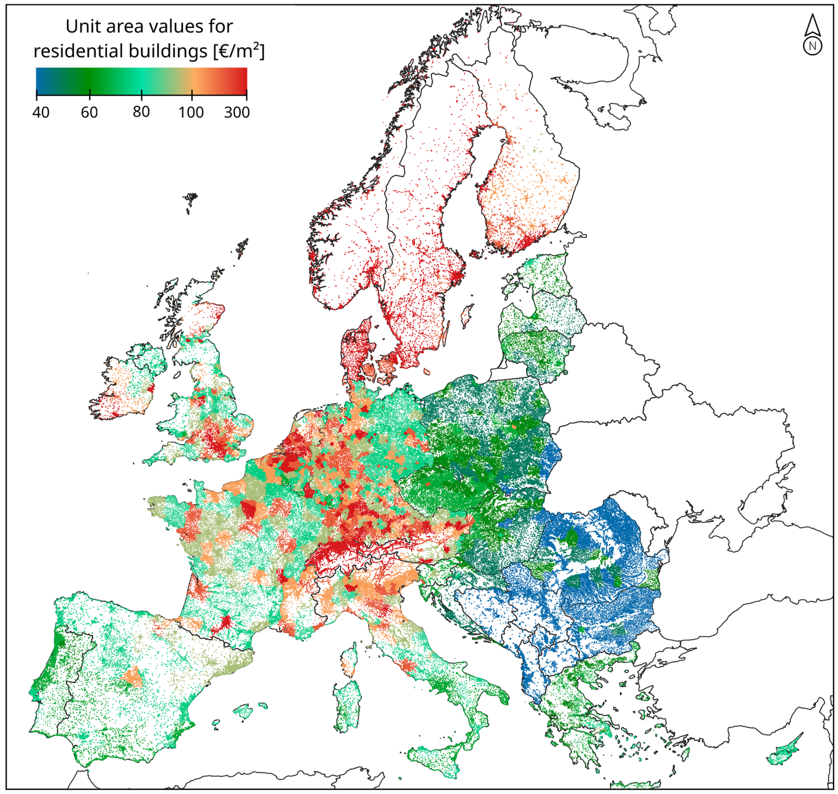

Figure 7. European asset map displaying the unit area values of residential buildings in 2013 in (euro/m^2) following the reconstruction costs approach.

3.1.2. Case Study Lech, Austria

The municipalities in the mountain basin of Reutte (catchment size of 1,000 km^2) in the Lech catchment (Austria) were affected by floods several times in the recent past, with severe flooding in 1999 and 2005 (Cammerer et al., 2013). The flood in 2005 caused direct loss of about 410 million euro (with 61% of loss in the private sector) in the entire federal state of Tyrol (Amt der Tiroler Landesregierung, 2006). In the case study area, the flood in August 2005 had a peak discharge of 943 m^3/s which corresponds to an estimated return period of 330 years at the gauge Lechaschau. Particularly, the municipalities of Pflach and Höfen were strongly affected, due to overtopping and breaches of embankments. The flood type can be regarded as an interaction of static and dynamic flooding in the case study area (Cammerer et al., 2013).

Official loss figure for validation: Estimation of structural loss to residential buildings in the study area is 1.9 million euro, as provided by Cammerer et al. (2013). This figure is based on official data but is associated with uncertainty, because loss reports did not differentiate well loss to building structure or contents. The study by Cammerer et al., 2013 made assumption to separate the aggregated loss figures but the true values are not reported.

Flood map: Maximum water depths of the flood event in August 2005 were simulated with hydrodynamic-numeric 2-D model Hydro_AS-2D. Two levee failures, which had occurred in the community of Pflach, were considered in the hydraulic simulation. While the simulation and validation were performed on a 1 m × 1 m grid, the used water depths were aggregated on a cell size of 10 m (Cammerer et al., 2013).

Empirical microscale loss data for model updating: To update the Bayesian Network model, local information of 22 households affected during the 2005 flood are available. In the Austrian federal states of Tyrol and Vorarlberg 218 interviews with private households were carried out in the aftermath of the flood event in 2005 in order to compare different risk transfer systems of three Alpine regions (Raschky et al., 2009). However, only 72 of all surveyed households were actually affected by the flood in 2005, and only 22 households provided enough information to estimate the relative loss. Additionally, the data contain information

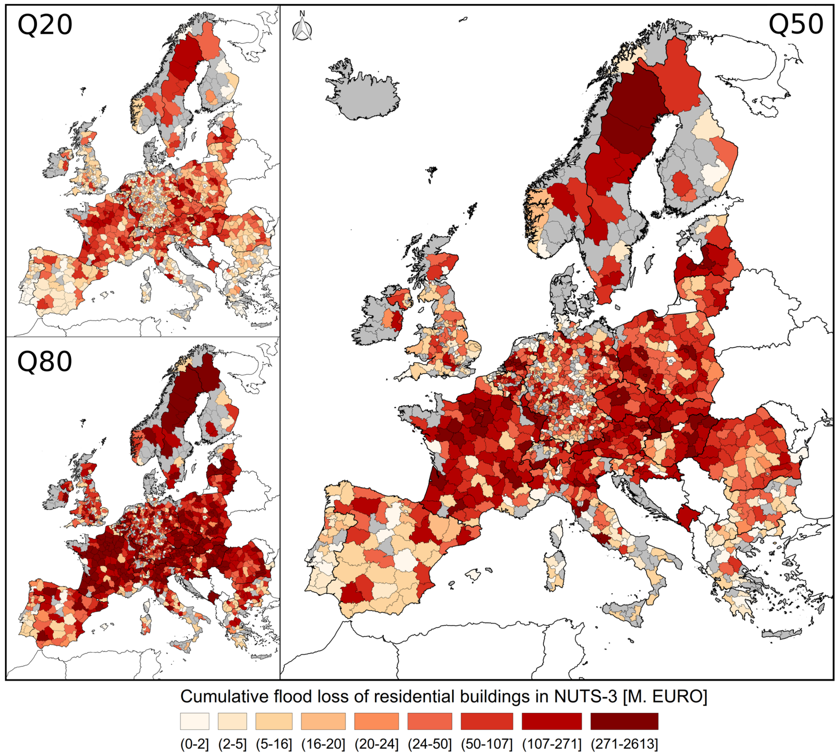

Figure 8. Maps of the cumulated flood loss of residential buildings for NUTS-3 regions in million euro. Gray NUTS-3 regions were not affected by the 100-year flood scenario or were not calculated due to lack of input data. Map of 20% quantile (left top), map of 80% quantile (left bottom), and map of 50% quantile (right).

about the inundation depth and duration, as well as the building area, building type, flood experience, and precautionary measures. Thus, in this case study, the flood intensity information used for model updating differs from the one used for model application.

3.1.3. Case Study Mulde, Germany

The Mulde catchment (7,400 km^2) in Saxony (Germany) is prone to recurrent flood hazards. During the last years it has been hit by severe floods in August 2002 and June 2013 (Conradt et al., 2012; Engel, 2004; Schröter et al., 2015). The flood in August 2002 was triggered by extreme precipitation in the headwater areas of the catchment. Record-breaking rainfall amounts of 312 mm were recorded within 24 hr at the station Zinnwald-Georgenfeld of the German Weather Service in the Ore Mountains (Ulbrich et al., 2003). As a result, extreme flash floods hit the upstream parts of the Mulde and its tributaries. The flood wave caused numerous dike breaches in the lower reach of the Mulde River with 19 municipalities affected. The magnitude of the flood peak discharge was in the order of a 500 year flood, estimated using methods of extreme value statistics based on annual maximum series of mean daily discharge records from the gauge Bad Dueben (Elmer et al., 2010).

Official loss figure for validation: Losses to residential buildings totaled 240.6 million euro (Saxon Relief Bank, 2005), for further details refer to (Kreibich, Botto, et al., 2017).

Flood map: For this event, an inundation depth map was derived from hydronumeric simulations (Apel et al., 2009) and hydraulic calculations (Grabbert, 2006). This map gives information on maximum inundation depths on a spatial grid with a pixel size of 10 m × 10 m.

Empirical microscale loss data for model updating: Local information from 74 households are available from the post-event computer-aided telephone interview survey for updating the Bayesian Network model (Thieken et al., 2017). The interview data set includes information about the building area, building type, flood experience, and precautionary measures. Also, the data about the inundation duration, and water depth at the building to characterize the flood intensity are available form the survey. Thus, in this case study, the flood information used for model updating differs from the one used for model application.

Table 2
Overview of Case Study Characteristics and Available Variables for Model Updating in the Case Studies

Case study characteristics	Caldogno	Lech	Mulde
Reported loss to residential buildings used for validation (M euro)	7.5	1.9	240
Number of empirical microscale observations available for updating	295	22	74
Inundated area (km^2)	3.3	3.4	116.5
Event year	2010	2005	2002
Availability of variables in microscale observations			
Water depth	✓	✓	✓
Duration	X	X	✓
Return period	✓	✓	✓
Building type	✓	X	✓
Building area	✓	X	✓
Flood experience	X	✓	✓
Precaution	X	✓	✓
Relative loss	✓	✓	✓

Note. The symbols indicate whether data were available (✓) or unavailable (X)

3.2. Updating Method Using Local Data

As described in section 2.1, the NPTs of the BN-FLEMOps model were trained based on empirical loss data from Germany. Bayesian networks offer the possibility to consistently update the NPTs with additional data, and Wagenaar et al. (2018) showed that such updating improves the spatial transferability of loss models at the microscale. This was explained by the fact, that the additional use of local data better enables the model to cover some effects of implicit assumptions about variables not included in the loss models, like flow velocity (Wagenaar et al., 2018). Thus, we test if the mesoscale application of the BN-FLEMOps model in geographical regions with potentially different socioeconomic, building and flood event characteristics can be improved via an updating of the NPTs with empirical data from the target regions. To assess the value of local data on the model performance, we use two update steps with 750 and 1,500 additional observations from the case study regions and compare it to the application of the general BN-FLEMOps model. Given, that the data set used to develop the NPTs of BN-FLEMOps consists of 1,522 observations, the update steps correspond to 50% and 100% of added data from the case study, respectively. That means, at the update step of 100%, the added data from the case study has as much weight to describe the damage processes as the German data used to derive the model.

Sampling with replacement is applied to generate the required number of 750 and 1,500 data points in the case study regions since in none of the areas enough empirical data is available (Table 2, second row). We follow the same approach as for the computation of loss ratios described in section 2.2.2, that is, the entire update and validation process is repeated 5,000 times.

In case the empirical data from the case study is not complete, the NPTs of the missing variables cannot be updated. In this case, the NPTs of these missing variables reproduce the joint probability distribution of the original model. This means that knowledge about the conditional probabilities between the loss influencing variables is transferred from the mesoscale model to the case study areas.

3.3. Result and Discussion of the Validation in the Three Case Study Areas

The results of the loss estimation with BN-FLEMOps on the mesoscale for the three case studies are shown in Figure 9 in comparison with the official loss figures. The thick solid line of the empirical cumulative density functions shows the median of the 5,000 repetitions of flood loss estimation. The red vertical solid lines indicate the officially reported loss for each case study. The mesoscale application of BN-FLEMOps yields results that are in the same order of magnitude as the reported loss values for all three case studies. Official loss figures are within the 95% quantile range of the probabilistic loss estimation. The loss estimation is however associated with large uncertainty manifest in the interquartile range in Table 3. For the Mulde case study, the median loss estimate shows an underestimation of about 104 million euro (43%). For the Caldogno and Lech case studies, we see an overestimation by the BN-FLEMOps model by 2.1 million

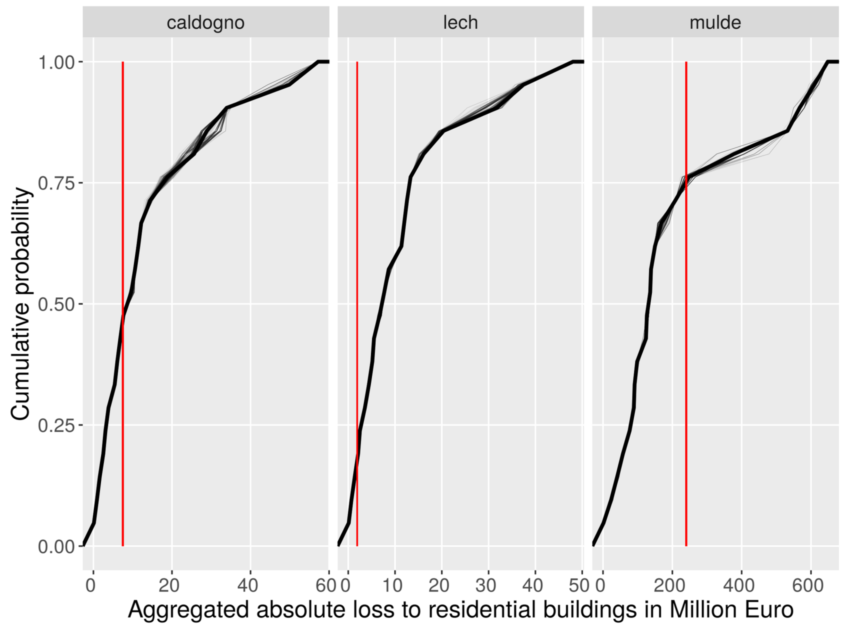

Figure 9. Empirical cumulative density function (ecdf) of the absolute residential building loss for the three case studies. The thick solid lines represent the median ecdf, while the gray lines represent the 1,000 model replications and red lines represent the official loss figure.

euro (28%) and 5.8 million euro (305%), respectively. We observe that the uncertainty of the upper tails of the loss distributions is larger than for the lower tails, which is shown by the variability between the loss estimation repetitions above the 75% quantile (Figure 9). This uncertainty is explained by multimodal marginal distributions for combinations of observations that lead to high loss ratios. Those multimodal marginal distributions are indicated by groups of deviating empirical cumulative density distributions of model replications in the (Figure 9). In addition, the model shows a strong sensitivity to the contribution of the highest loss class. This can be attributed to the discretization of the variable relative building loss. The highest loss class covers a very large range, from 0.274 to 1. We use the median as the representative value for every class to compute the absolute damage (assuming a uniform distribution within each class). The representative value for the highest loss class is 0.637 whereas the representative value for the second highest loss class is 0.226, which is a difference of more than 40 percent relative building loss. This effect stems from the discretization of the continuous variables and is a known issue and subject to ongoing research.

Using the median of the 5,000 repetitions of the loss estimations (thick solid line in Figure 9), the interquartile range (0.25 to 0.75) of the simulation covers the official loss figure for the Mulde and Caldogno cases, but not for the Lech case study where the overestimation is too high (Table 3). The underestimation of BN-FLEMOps in the Mulde case study may partly be attributed to uncertainties in the temporal transfer of the asset values to the year 2002 as discussed in section 2.3.1. The BN-FLEMOps shows the poorest performance in the Lech case study and the best performance in the Caldogno case study. The mesoscale loss estimation approach developed for the whole of Europe seems to be less suitable for data-scarce applications and low impact events like the Lech case study where damage to only 22 objects was reported.

The loss estimates with the mesoscale application of BN-FLEMOps for the Lech case study are high also in comparison with the results achieved by Cammerer et al. (2013). They tested several international flood loss models in a spatial transfer study, which resulted in a broad range of loss estimates from 0.842 million euro (based on model MURL, 2002) to 9.094 million euro (based on model Hydrotec (2002) when applied to the same inundation area as used in this study. However, Cammerer et al. (2013) concluded, that models based on neighboring regions with similar building and flood event characteristics yield fundamentally better results than models based on loss data from spatially different regions and dissimilar flood events. Given

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Table 3
Comparison of Average Loss Estimate From BN-FLEMOps and Official Loss Information

Case studies	Median loss estimate + (IQR) in million euro	Official loss in million euro
Caldogno (Italy)	9.6 (3.8; 18.8)	7.5
Lech (Austria)	7.7 (3.6; 13.3)	1.9
Mulde (Germany)	136.0 (89.0; 248.2)	240.0

Note. IQR = interquartile range.

this hypothesis, they identified the most suitable models estimating loss between 1.836 million and 2.854 million euro.

For the 2010 flood in the Caldogno case study, the mesoscale application of BN-FLEMOps achieves equally good results as previous studies. Scorzini and Frank (2017) show a comprehensive overview of different model applications and flood loss estimates for the city of Caldogno ranging from 5.96 million euro (model based on Debo, 1982) to 13.49 million euro (model based on Dutta et al., 2003).

The Mulde flood event was studied by Kreibich, Botto, et al. (2017), who developed a mesoscale model that was applied and validated in the different municipalities affected by the flood event. Their aggregated loss for all municipalities sums up to 238.6 million euro and is thus very close to the reported loss of 240 million euro. However, also this study reported a high uncertainty in loss estimation with values between 44 million and 400 million euro and used a different data source for asset values (Kreibich, Botto, et al., 2017).

3.4. Result and Discussion of Model Adaptation Test

Previous studies have shown that spatial transfer of flood loss models may entail a decline in model predictive performance and an increase of model uncertainty (e.g., Cammerer et al., 2013; Schröter et al., 2014). Wagenaar et al. (2018) report that BN-FLEMOps can be applied in regions different from its origin while maintaining a stable performance. To further test the spatial transferability of the BN-FLEMOps and compare performance on the microscale and mesoscale, the model is adapted to the different case studies via updating of the NPTs with empirical microscale loss data from each case study. Figure 10 shows the median and the 90% quantile range for the application of the mesoscale BN-FLEMOps model (0 data points used for NPT update) and the two update steps (750 and 1,500 data points used for NPT update). The officially reported loss is depicted as a red line. In the Caldogno and Mulde case studies, the loss estimates improve

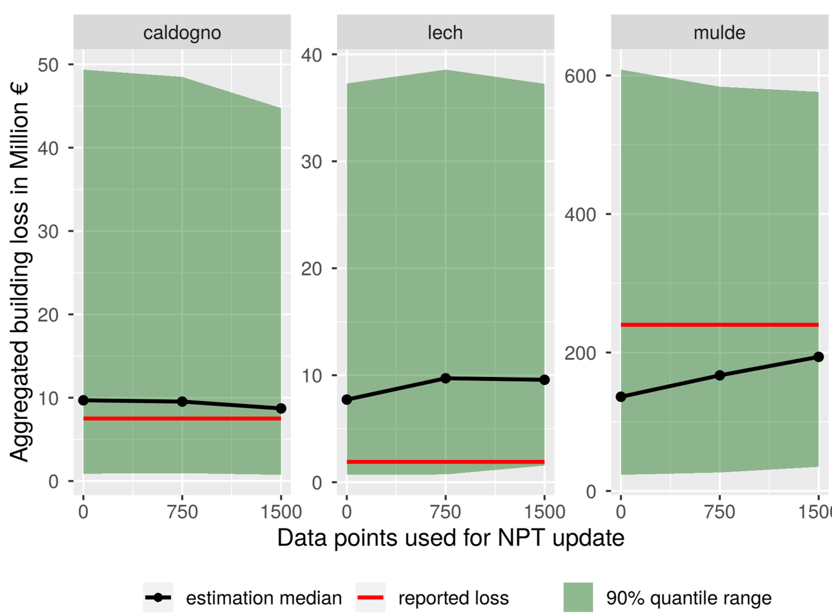

Figure 10. Comparison of reported loss and estimated loss for the application of BN-FLEMOps with update.

with updating, which is reflected by slightly decreasing the 90% quantile ranges and an approximation of the median loss estimate to the official loss figure. In the Caldogno case study, the median of the simulated loss is 8.7 million euro for the second updating step (1500 data points added), which reduced the overestimation from 28% to 16%. For the Mulde case study, the median simulated loss increased with the first and second update step to 161.5 million and 199.7 million euro, respectively. That reduced the underestimation from the initial 43% to 33% for the first update step and to 19% for the second one. The results for the Lech case study do not improve with updating since the estimation for the simulated loss is even increasing with updating and thus the overestimation is increasing. We attribute the failure of the updating process mainly to the very limited number of empirical loss data available in the Lech case study. With only 22 loss data points as the base population, the information content about local damage processes is rather limited. Further tests are necessary to identify the boundary conditions for a successful model. The performance of the BN-FLEMOps model in these case studies is comparable to other models, except for the Lech. For the Caldogno case study, the average of seven microscale models yields a 10% overestimation of reported loss (Scorzini & Frank, 2017). The application of six other mesoscale loss models to the Mulde case study resulted in an average underestimation of 16% (Kreibich, Botto, et al., 2017). For the Lech case study, the site-specific mesoscale model $\text{FLEMO}_{\text{AT+}}$ covers the observed loss within the 95% confidence interval which is also clearly more narrow (1.872–2.343 million euro) (Cammerer et al., 2013) than for the BN-FLEMOps model. These numbers illustrate that the BN-FLMOps model provides comparable outcomes. A closely related question concerns the effort of transferring the BN-FLEMOps and other models to other contexts. While the site specific implementation of flood loss models requires the acquisitions and compilation of various input data sets, for the BN-FLMOps model the building resistance-related mesoscale proxy variables flood experience and building area have been consistently derived for the whole of Europe and will be accessible via online data repositories. This will reduce the effort to apply the BN-FLEMOps model throughout Europe.

4. Conclusion

The developed approach for a consistent flood loss modeling in Europe, which is based on the probabilistic, multivariable BN-FLEMOps is suitable for loss estimation of residential building structures in the whole of Europe. This novel approach advances flood loss modeling since it enables a consistent estimation of losses on a continental scale with the resulting probabilistic loss estimates inherently providing uncertainty information. Such uncertainty information can significantly improve the quality of decisions, for example, about different risk management strategies based on cost-benefit analyses since the uncertainty information enables decision makers to consider the whole range of possible outcomes. Depending on risk-averse or risk-neutral attitudes of the decision makers, different alternatives might be preferred. Additionally, the credibility and trust in risk analyses can be preserved, since the impression of certain estimates is avoided and uncertainties in the results are communicated clearly.

BN-FLEMOps can be adapted to individual regions in Europe with an updating approach using empirical data from the target region. This approach is validated in three case studies of varying spatial scale in Germany, Italy, and Austria. In two of the three case studies, the performance of the model improved further with this updating. However, results indicate that the mesoscale approach may be less suitable for data-scarce, low-impact events like in the Austrian Lech case study, where the damage to only 22 objects amounts to a comparably small loss figure of 1.9 million euro. Given the shortage of detailed empirical flood loss data for model updating, further tests with respect to adapting the model to different European regions are recommended to better understand and characterize the circumstances under which the updating approach improves model performance. Nevertheless, the proposed approach for probabilistic flood loss modeling in Europe can provide estimates of flood loss that reliably cover reported figures in the 95% quantile range.

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References

Alfieri, L., Feyen, L., & Di Baldassarre, G. (2016). Increasing flood risk under climate change: A pan-European assessment of the benefits of four adaptation strategies. *Climatic Change*, *136*(3-4), 507–521. https://doi.org/10.1007/s10584-016-1641-1

Alfieri, L., Salamon, P., Bianchi, A., Neal, J., Bates, P., & Feyen, L. (2014). Advances in pan-European flood hazard mapping. *Hydrological Processes*, *28*(13), 4067–4077. https://doi.org/10.1002/hyp.9947

Alfieri, L., Feyen, L., Dottori, F., & Bianchi, A. (2015). Ensemble flood risk assessment in Europe under high end climate scenarios. *Global Environmental Change*, *35*, 199–212. https://doi.org/10.1016/j.gloenvcha.2015.09.004

Amt der Tiroler Landesregierung (2006). *Rechnungsabschluss 2005 Des Landes Tirol*. Innsbruck: Landesrechnungshof.

Apel, H., Aronica, G. T., Kreibich, H., & Thieken, A. H. (2009). Flood risk analyses—How detailed do we need to be? *Natural Hazards*, *49*(1), 79–98. https://doi.org/10.1007/s11069-008-9277-8
Barrington-Leigh, C., & Millard-Ball, A. (2017). The world's user-generated road map is more than 80% complete. *PLoS ONE*, *12*(8), 1, e0180698–20. https://doi.org/10.1371/journal.pone.0180698
Brakenridge, G. R. (2018). Global active archive of large flood events. Retrieved from http://floodobservatory.colorado.edu/Archives/index.html
de Brito, M. M., & Evers, M. (2016). Multi-criteria decision-making for flood risk management: A survey of the current state of the art. *Natural Hazards and Earth System Sciences*, *16*(4), 1019–1033. https://doi.org/10.5194/nhess-16-1019-2016
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
Conradt, T., Roers, M., Schröter, K., Elmer, F., Hoffmann, P., Koch, H., et al. (2012). Vergleich der Extremhochwässer 2002 und 2013 im deutschen Teil des Elbegebiets und deren Abflusssimulation durch SWIM-live. *Hydrologie und Wasserbewirtschaftung*, *56*(3), 241–245. https://doi.org/10.5675/HyWa_2013,5_4
Cortès, M., Turco, M., Llasat-Botija, M., & Llasat, M. C. (2018). The relationship between precipitation and insurance data for floods in a Mediterranean region (Northeast Spain). *Natural Hazards and Earth System Sciences*, *18*(3), 857–868. https://doi.org/10.5194/nhess-18-857-2018
Debo, T. N. (1982). Urban flood damage estimating curves. *Journal of the Hydraulics Division*, *108*(10), 1059–1069. Retrieved from http://cedb.asce.org/CEDBsearch/record.jsp?dockey=0034635
Dottori, F., Figueiredo, R., Martina, M. L. V., Molinari, D., & Scorzini, A. R. (2016). INSYDE: A synthetic, probabilistic flood damage model based on explicit cost analysis. *Natural Hazards and Earth System Sciences*, *16*(12), 2577–2591. https://doi.org/10.5194/nhess-16-2577-2016
Dottori, F., Kalas, M., Salamon, P., Bianchi, A., Alfieri, L., & Feyen, L. (2017). An operational procedure for rapid flood risk assessment in Europe. *Natural Hazards and Earth System Sciences*, *17*(7), 1111–1126. https://doi.org/10.5194/nhess-17-1111-2017
Dutta, D., Herath, S., & Musiake, K. (2003). A mathematical model for flood loss estimation. *Journal of Hydrology*, *277*(1-2), 24–49. https://doi.org/10.1016/S0022-1694(03)00084-2
EEA, (European Environment Agency). (2010). Mapping the impacts of recent natural disasters and technological accidents in Europe—An overview of the last decade (No. 978-92-9213-168-5) (pp. 47 S.-47 S.). https://doi.org/10.2800/62638
EEA, (European Environment Agency). (2016). Corine Land Cover (CLC) 2012, Version 18.5.1, seamless vector data. Retrieved from https://land.copernicus.eu/pan-european/corine-land-cover/clc-2012?tab=download
Elmer, F., Thieken, A. H., Pech, I., & Kreibich, H. (2010). Influence of flood frequency on residential building losses. *Natural Hazards and Earth System Science*, *10*(10), 2145–2159. https://doi.org/10.5194/nhess-10-2145-2010
Engel, H. (2004). The flood event 2002 in the Elbe river basin, causes of the flood, its course, statistical assessment and flood damages. *La Houille Blanche*, *6*(6), 33–36. https://doi.org/10.1051/lhb:200406003
EU, (European Union). directive 2007/60/EC of the European parliament and of the council of 23 October 2007 on the assessment and management of flood risks, 288 § (2007).
Eurostat. (2018). Gross domestic product (GDP) at current market prices by NUTS 3 regions. Retrieved 30 November 2018, from http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10r_3gdp&lang=en
Fenton, N., & Neil, M. (2013). *Risk Assessment and Decision Analysis with Bayesian Networks*. Boca Raton: CRC Press.
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
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), 1, e0159791–22. https://doi.org/10.1371/journal.pone.0159791
Grabbert, J.-H. (2006). *Analyse der schadensbeeinflussenden Faktoren des Hochwassers 2002 und Ableitung eines mesoskaligen Abschätzungsmodells für Wohngebäudeschäden* (Thesis). Potsdam: University of Potsdam.
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
Hochrainer, S., Linnerooth-Bayer, J., & Mechler, R. (2010). The European Union solidarity fund. *Mitigation and Adaptation Strategies for Global Change*, *15*(7), 797–810. https://doi.org/10.1007/s11027-009-9209-2
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
Huizinga, J. (2007). *Flood damage functions for EU member states*. Lelystad, the Netherlands: HKV Lijn in water.
Huizinga, J., Moel, H. D., & Szewczyk, W. (2017). Global Flood Depth-Damage Functions Database with Guidelines. https://doi.org/10.2760/16510
Jongman, B., Hochrainer-Stigler, S., Feyen, L., Aerts, J. C. J. H., Mechler, R., Botzen, W. J. W., et al. (2014). Increasing stress on disaster-risk finance due to large floods. *Nature Climate Change*, *4*(4), 264–268. https://doi.org/10.1038/nclimate2124
Jongman, B., Kreibich, H., Apel, H., Barredo, J. I., Bates, P. D., Feyen, L., et al. (2012). Comparative flood damage model assessment: Towards a European approach. *Natural Hazards and Earth System Science*, *12*(12), 3733–3752. https://doi.org/10.5194/nhess-12-3733-2012
Kreibich, H., Botto, A., Merz, B., & Schröter, K. (2017). Probabilistic, multivariable flood loss modeling on the mesoscale with BT-FLEMO. *Risk Analysis*, *37*(4), 774–787. https://doi.org/10.1111/risa.12650
Kreibich, H., Bubeck, P., Van Vliet, M., & De Moel, H. (2015). A review of damage-reducing measures to manage fluvial flood risks in a changing climate. *Mitigation and Adaptation Strategies for Global Change*, *20*(6), 967–989. https://doi.org/10.1007/s11027-014-9629-5
Kreibich, H., Piroth, K., Seifert, I., Maiwald, H., Kunert, U., Schwarz, J., et al. (2009). Is flow velocity a significant parameter in flood damage modelling? *Natural Hazards and Earth System Sciences*, *9*(5), 1679–1692. https://doi.org/10.5194/nhess-9-1679-2009
Kreibich, H., Schröter, K., & Merz, B. (2016). Up-scaling of multi-variable flood loss models from objects to land use units at the meso-scale. *Proceedings of the International Association of Hydrological Sciences*, *373*, 179–182. https://doi.org/10.5194/piahs-373-179-2016
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., Haubrock, S., & Schröter, K. (2017). HOWAS21, the German flood damage database. In D. Molinari, S. Menoni, & F. Ballio (Eds.), *Flood damage survey and assessment: New insights from research and practice*, (pp. 65–75). Washington, DC: Wiley. http://doi.org/10.1002/9781119217930.ch5

Kron, W. (2005). Modellierung des Überschwemmungsrisikos in der Versicherungswirtschaft. Hydrologische Wissenschaft Fachgemeinschaft in Der DWA, (08.05), 93-112. Retrieved from https://nordsee.lfi.rwth-aachen.de/fghw-uploads/fghw-hefte/08.05.pdf#page=93

Kunreuther, H., Heal, G., Allen, M., Edenhofer, O., Field, C. B., & Yohe, G. (2013). Risk management and climate change. *Nature Climate Change*, *3*(5), 447–450. https://doi.org/10.1038/nclimate1740

Lauritzen, S. L. (1996). *Graphical Models*. Oxford, New York: Oxford University Press.

Lüdtke, S., Steinhausen, M., Schröter, K., Figueiredo, R., & Kreibich, H. (2019). Pan-European probabilistic flood loss data forresidential buildings. GFZ Data Services. https://doi.org/10.5880/GFZ.4.4.2019.002

Merz, B., Kreibich, H., & Lall, U. (2013). Multi-variate flood damage assessment: A tree-based data-mining approach. *Natural Hazards and Earth System Science*, *13*(1), 53–64. https://doi.org/10.5194/nhess-13-53-2013

Merz, B., Kreibich, H., Schwarze, R., & Thieken, A. (2010). Review article 'assessment of economic flood damage'. *Natural Hazards and Earth System Science*, *10*(8), 1697–1724. https://doi.org/10.5194/nhess-10-1697-2010

Merz, B., Kreibich, H., Thieken, A., & Schmidtke, R. (2004). Estimation uncertainty of direct monetary flood damage to buildings. *Natural Hazards and Earth System Science*, *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

de Moel, H., & Aerts, J. C. J. H. (2011). Effect of uncertainty in land use, damage models and inundation depth on flood damage estimates. *Natural Hazards*, *58*(1), 407–425. https://doi.org/10.1007/s11069-010-9675-6

de Moel, H., Jongman, B., Kreibich, H., Merz, B., Penning-Rowsell, E., & Ward, P. J. (2015). Flood risk assessments at different spatial scales. *Mitigation and Adaptation Strategies for Global Change*, *20*(6), 865–890. https://doi.org/10.1007/s11027-015-9654-z

Mooney, P., & Minghini, M. (2017). A Review of OpenStreetMap Data. In G. Foody, L. See, S. Fritz, P. Mooney, A.-M. Olteanu-Raimond, C. C. Fonte, & V. Antoniou (Eds.), *Mapping and the Citizen Sensor* (pp. 37–59). London: Ubiquity Press. https://doi.org/10.5334/bbf.c

Murphy, K. (2012). *Machine Learning: A Probabilistic Perspective*. Adaptive computation and machine learning: MIT Press.

OSM contributors. (2018a). OpenStreetMap. Retrieved 30 November 2018, from https://www.openstreetmap.org/copyright/en

OSM contributors. (2018b). OpenStreetMap. Retrieved 30 November 2018, from https://www.openstreetmap.org/

Pappenberger, F., & Beven, K. J. (2006). Ignorance is bliss: Or seven reasons not to use uncertainty analysis. *Water Resources Research*, *42*, W05302. https://doi.org/10.1029/2005WR004820

Pearl, J. (1988). *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

Penning-Rowsell, E., Johnson, C., Tunstall, S., Tapsell, S., Morris, J., Chatterton, J., et al. (2005). *The Benefits of Flood and Coastal Risk Management: A Manual of Assessment Techniques (Multi-Coloured Handbook 2005)*. London: Middlesex University Press.

Penning-Rowsell, E. C., & Green, C. (2000). New insights into the appraisal of flood-alleviation benefits: (1) flood damage and flood loss information. *Water and Environment Journal*, *14*(5), 347–353. https://doi.org/10.1111/j.1747-6593.2000.tb00272.x

Raschky, P., Schwarze, R., Schwindt, M., & Weck-Hannemann, H. (2009). *Alternative Finanzierungs- und Versicherungslösungen - Vergleich unterschiedlicher Risikotransfersysteme dreier vom Augusthochwasser 2005 betroffener Länder: Deutschland, Österreich und Schweiz (Analysebericht) (P. 28)*. Bern: Präventionsstiftung der Kantonalen Gebäudeversicherungen.

Regione del Veneto. (2011a). 31 ottobre-2 novembre 2010: l'alluvione dei Santi (no. Rapporto Statistico 2011) (pp. 410-425). Retrieved from http://statistica.regione.veneto.it/Pubblicazioni/RapportoStatistico2011/Capitolo17.html

Regione del Veneto. (2011b). La grande alluvione. Retrieved from http://www.regione.veneto.it/web/guest/comunicati-stampa/dettaglio-comunicati?_spp_detailId=361297

Sairam, N., Schröter, K., Lüdtke, S., Merz, B., & Kreibich, H. (2019). Quantifying flood vulnerability reduction via private precaution. *Earth's future*, *7*(3), 235–249. http://doi.org/10.1029/2018EF000994

Saxon Relief Bank, (SAB). (2005, February). Schäden durch das Hochwasser 2002. Angaben aus der Fördermitteldatenbank [Damages of the Flood 2002. Data from the Compensation Data Bank].

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.Received

Schröter, K., Kunz, M., Elmer, F., Mühr, B., & Merz, B. (2015). What made the June 2013 flood in Germany an exceptional event? A hydro-meteorological evaluation. *Hydrology and Earth System Sciences*, *19*(1), 309–327. https://doi.org/10.5194/hess-19-309-2015

Schröter, K., Lüdtke, S., Redweik, R., Meier, J., Bochow, M., Ross, L., et al. (2018). Flood loss estimation using 3D city models and remote sensing data. *Environmental Modelling & Software*, *105*, 118–131. https://doi.org/10.1016/j.envsoft.2018.03.032

Scorzini, A. R., & Frank, E. (2017). Flood damage curves: New insights from the 2010 flood in Veneto, Italy. *Journal of Flood Risk Management*, *10*(3), 381–392. https://doi.org/10.1111/jfr3.12163

Scutari, M., & Denis, J.-B. (2014). *Bayesian Networks*. Chapman & Hall/CRC Texts in Statistical Science. Boca Raton: Chapman and Hall/CRC. https://doi.org/10.1201/b17065

Smith, D. (1994). Flood damage estimation—A review of urban stage-damage curves and loss functions. *Waster SA*, *20*(3), 231–238.

Spekkers, M. H., Clemens, F. H. L. R., & ten Veldhuis, J. A. E. (2015). On the occurrence of rainstorm damage based on home insurance and weather data. *Natural Hazards and Earth System Sciences*, *15*(2), 261–272. https://doi.org/10.5194/nhess-15-261-2015

Thieken, A., Kreibich, H., Müller, M., & Lamond, J. (2017). *Data Collection for a Better Understanding of What Causes Flood Damage—Experiences with Telephone Surveys*, (pp. 95–106). Washington, DC: https://doi.org/10.1002/9781119217930.ch7

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

Ulbrich, U., Brücher, T., Fink, A. H., Leckebusch, G. C., Krüger, A., & Pinto, J. G. (2003). The central European floods of August 2002: Part 2—Synoptic causes and considerations with respect to climatic change. *Weather*, *58*(11), 434–442. https://doi.org/10.1256/wea.61.03B

Van Renssen, S. (2013). EU adaptation policy sputters and starts. *Nature Climate Change*, *3*(7), 614–615. https://doi.org/10.1038/nclimate1943

Vogel, K., Riggelsen, C., Scherbaum, F., Schröter, K., Kreibich, H., & Merz, B. (2013). Challenges for Bayesian Network Learning in a Flood Damage Assessment Application, (June). https://doi.org/10.1201/b16387-452

Vogel, K., Weise, L., Schröter, K., & Thieken, A. H. (2018). Identifying driving factors in flood-damaging processes using graphical models. *Water Resources Research*, *54*(11), 8864–8889. https://doi.org/10.1029/2018WR022858

Wagenaar, D., De Jong, J., & Bouwer, L. M. (2017). Multi-variable flood damage modelling with limited data using supervised learning approaches. *Natural Hazards and Earth System Sciences*, *17*(9), 1683–1696. https://doi.org/10.5194/nhess-17-1683-2017

10.1029/2019WR026213

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*(5), 3688–3703. https://doi.org/10.1029/2017WR022233

Wind, H. G., Nierop, T. M., de Blois, C. J., & de Kok, J. L. (1999). Analysis of flood damages from the 1993 and 1995 Meuse floods. *Water Resources Research*, *35*(11), 3459–3465. https://doi.org/10.1029/1999WR900192

Zhai, G., Fukuzono, T., & Ikeda, S. (2005). Modeling flood damage: Case of Tokai flood 2000. *Journal of the American Water Resources Association*, *41*(1), 77–92. https://doi.org/10.1111/j.1752-1688.2005.tb03719.x