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COMPREHENSIVE REVIEW

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Toward an adequate level of detail in flood risk assessments

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Abstract

Flood risk assessments require different disciplines to understand and model the underlying components hazard, exposure, and vulnerability. Many methods and data sets have been refined considerably to cover more details of spatial, temporal, or process information. We compile case studies indicating that refined methods and data have a considerable effect on the overall assessment of flood risk. But are these improvements worth the effort? The adequate level of detail is typically unknown and prioritization of improvements in a specific component is hampered by the lack of an overarching view on flood risk. Consequently, creating the dilemma of potentially being too greedy or too wasteful with the resources available for a risk assessment. A "sweet spot" between those two would use methods and data sets that cover all relevant known processes without using resources inefficiently. We provide three key questions as a qualitative guidance toward this "sweet spot." For quantitative decision support, more overarching case studies in various contexts are needed to reveal the sensitivity of the overall flood risk to individual components. This could also support the anticipation of unforeseen events like the flood event in Germany and Belgium in 2021 and increase the reliability of flood risk assessments.

KEYWORDS

decision support, extreme events, integrated flood risk management, risk assessment

1 | INTRODUCTION

Floods pose an imminent risk to societies around the world. In 2020, numerous flood events hit countries of almost all continents (Floodlist, 2021; floodlist.com). In the aftermath, these countries suffered from humanitarian emergencies and economic impacts. The Emergency Events Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters (CRED) recorded economic flood damage of US$ 651 billion between 2000 and 2019 worldwide. Exactly 1.6 billion people were affected by floods. Worldwide, no other hazard has affected as many people (UNDRR & CRED, 2020). Mitigating flood disaster risk is thus of high societal relevance. Accurate flood risk assessments, tailored to the specific decision context, are required to inform mitigation strategies.

Usually, flood risk is conceptualized as the interplay between the three components: hazard, the flood-exposed elements, and their vulnerability toward flooding. The quantification of each of the components has undergone substantial development during the last years regarding the details in their models and data sets, mostly by increasing the spatial and temporal resolution or a more in-depth description of processes. For example, inundation processes are increasingly simulated with very high space–time resolution allowing them to represent highly dynamic and local flow situations (de Almeida et al., 2018). Exposed elements are more and more identified with object-specific data sets instead of aggregated land use data (Pittore et al., 2017; Wieland & Pittore, 2017) leading to increased spatial resolutions of exposure assessments. Models describing the flood vulnerability of economic assets have increasingly incorporated a wider range of damage drivers (Carisi et al., 2018; Wagenaar et al., 2018).

An increasing level of detail is usually considered as an important step toward a more accurate risk assessment (Klijn et al., 2015; Thieken, Kienzler, et al., 2016) and effective cost–benefit analyses (Woodward et al., 2014). The influence of changes in a single component on the risk is often investigated with sensitivity analyses. Thomas Steven Savage et al. (2016) and Xing et al. (2021), for example, quantify the sensitivity of hydraulic models to different factors, such as the spatial resolution, finding that the importance varies with the context and the model output. Bermudez and Zischg (2018) show that the representation of buildings has a strong influence on the attribution of water levels to the buildings in micro-scale flood risk assessments. Schröter et al. (2014) find that more complex flood damage models show improved performance and transferability. Some studies investigate uncertainties and different data sets of all components. Winter et al. (2019) conclude that different model assumptions in each component have the potential to change the risk estimates considerably. Tate et al. (2015) come to a similar conclusion for the HAZUS model.

Despite these advancements, the flood event in Germany and Belgium in July 2021 demonstrated that flood events can still be surprising and tremendously underestimated in their intensity and potential impacts. On the July 14, 2021 the low-pressure system Bernd triggered flood events, flash floods, and mass movements in Germany and its neighboring countries (Dietze & Öztürk, 2021). In Germany, the event caused 189 fatalities and 33 billion Euro damage exceeding the impacts of the flood events in 2002 and 2013 (DKKV, 2022). The event went beyond the expected flood-prone areas identified by the flood risk assessment done beforehand in the frame of the European Floods Directive. Catastrophic events like these show that risk assessments need to be constantly updated and improved. Yet, the ideal level of details required for a reliable risk assessment is typically unknown and the role of additional details on the overall flood risk is rarely discussed.

In this article, we aim at discussing the details needed for a flood risk assessment considering three key questions for guidance.

1. Which processes are relevant in the context at hand? The essential processes depend largely on the objectives of the risk assessment. It is worthwhile to define essential processes and to add or remove the ones with substantial or negligible effects on the outcome. Hidden processes which are not considered in the assessment or cannot be described by the models but could potentially lead to huge impacts and hence should also be thought of to prevent possible surprises (Merz et al., 2015).
2. Which (temporal) dynamics are relevant? Short- and long-term dynamics need to be differentiated here. Short-term temporal dynamics include, for example, the timing and the rapidness of events and their effect on the timing of early warning. Another aspect is the dynamic of several consecutive events or even events triggering each other (Pescaroli & Alexander, 2018). These dynamics can have a tremendous influence on the risk and the impacts on society, for example, through a failure of critical infrastructure such as bridges. Long-term dynamics can be changes in the catchment, for example, through changes in land use, or the societal and natural systems, for example, with changing precipitation patterns.
3. Which spatial and temporal resolution is needed? The choice of data and methods and their spatial and/or temporal resolution strongly determine the processes which can be described and should therefore be in accordance with the objectives (e.g., Apel et al., 2009; Wünsch et al., 2009). This influence has to be known and possibly alternatives to the chosen data and methods need to be considered. The spatial and/or temporal resolution of the results should correspond to the needs of the decision process at hand.

We illustrate the importance of these questions exemplarily by selected case studies. These case studies evaluate developments of single risk components and discuss the relevance of different levels of detail for the final risk assessment. Despite the typical limitations of case studies due to their specific conditions such as the study region or the research questions they were designed to answer, we think that case studies in conjunction with literature can be of value for a broader discussion on details in flood risk assessments.

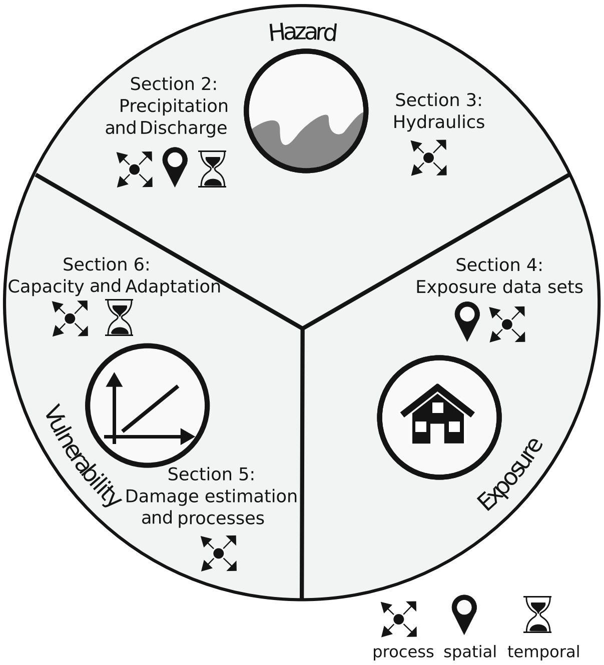

FIGURE 1 Overview of the sections organized along the flood risk components hazard, exposure, and vulnerability. The icons indicate the improvements of details with regard to process, spatial, or temporal information discussed in the specific sections.

In this regard, we consider rainfed flood types, namely river, pluvial, and flash floods. The case studies deal with developments (spatial, temporal, process details) in specific topics from one of the risk components, beginning from precipitation, discharge generation, and hydraulics over exposed assets to damage processes and finally societies' adaptation to flood events. Figure 1 gives an overview of the structure of this study. Each section shortly recapitulates developments in the last 10–15 years in a brief review in the beginning, followed by a case study that shows the relevance of more details in this domain for flood risk assessments. The literature search for the reviews is based on searches in the Web of Knowledge and was driven by the expert knowledge of the authors. The findings of the sections are then synthesized in a joint discussion.

2 | PRECIPITATION AND DISCHARGE

Meteorological conditions, particularly precipitation or snow melt, are the source for the generation of any flood event. A change in the features of precipitation, for instance with progressing global change, are likely to impact the flood types as well (Blöschl et al., 2017; Bronstert et al., 2002; Kemter et al., 2020; Vormoor et al., 2015). From long-term observation series with appropriately high temporal resolutions in Western Europe (Bürger et al., 2014; Haerter et al., 2010; Lenderink & van Meijgaard, 2008), Canada (Panthou et al., 2014), the United States (Mishra et al., 2012), and Australia (Hardwick et al., 2010) it was found that extreme precipitation intensities increase in hourly or shorter sums by ~7% per 1 K warming.

Intensity–duration–frequency (IDF) curves represent the relation between rainfall duration, intensity, and local occurrence probability. They provide the information required for estimates of extreme discharge to design drainage systems, protection measures, water, and flood management structures (Bürger et al., 2021; Chow, 1953; Ulrich et al., 2020). Usually, these relations are estimated pointwise and from annual maxima, that is, using data of a single rain gauge, and they include both short- and long-lasting rainfall events (from a few minutes up to several days). As precipitation means and also extremes are expected to alter in a changing climate (e.g., IPCC, 2018; Lehmann et al., 2018), we can expect IDF relations to change as well. Long records with (sub-)hourly resolution are necessary as they are typically based on annual (or monthly) maxima of precipitation sums for minutes (or at least hours) up to days. Thus, only regional case studies are available on changing IDF relations in a changing climate, showing that changes in extremes depend on the duration of the event, that is, the physical process behind (e.g., Cheng & AghaKouchak, 2014; Sarhadi & Soulis, 2017). Furthermore, using seasonal or even monthly maxima allows a more detailed discussion of the behavior of extremes of different durations, at least in the mid-latitudes this separates convective from frontal processes to a large extend (Ulrich et al., 2021) and gives rise to more complex models for IDF curves, describing more details (Fauer et al., 2021). Insights beyond the regional scale require extensive data sets with a high spatio-temporal resolution.

Apart from the meteorological conditions, both catchment surface and river hydraulic conditions are further key elements in the generation and routing processes of discharge (Rogger et al., 2017). The runoff generation conditions evolve through a combination of soils, vegetation, topography, and anthropogenic impacts. Thus, changes in catchment surface conditions may have a direct influence on the amount of runoff generated, and therefore influence flash flood occurrence, frequency, and magnitude; and are typically of lesser relevance for river floods (Niehoff et al., 2002; Rogger et al., 2017). In addition, other mechanisms in the river corridor like clogging of river cross-sections or culverts by sediment obstructions, floating debris, and wood at bridges, flow obstacles in the river course due to landslides or ice blockages, or failure of flood protection measures, may aggravate local flooding (Bronstert et al., 2020).

Besides this wide range of processes, there is also a wide spectrum of methods to estimate the probability of certain flood discharges, that is, the flood frequency curve. The spectrum ranges from purely statistical approaches, based on extreme value statistics (e.g., Stedinger, 2017) to simulation approaches, either event-based or based on continuous simulation (e.g., Falter et al., 2015; Rogger et al., 2012; Winter et al., 2019). Limiting the discussion to the statistical approaches, we find that the perspective of the pioneers of flood frequency analysis (e.g., Gumbel, 1941) has been considerably widened by regional approaches (e.g., Hosking & Wallis, 1997), by applying multivariate analyses (e.g., Chowdhary & Singh, 2019), by exploiting historical and paleo data (e.g., Kjeldsen et al., 2014), and by including non-stationarity (e.g., Serago & Vogel, 2018) and process knowledge (e.g., Viglione et al., 2013). Taking a catchment-perspective, Merz and Blöschl (2003) classified more than 11,500 flood events for 490 Austrian catchments into five process types: long-rain floods, short-rain floods, flash floods, rain-on-snow floods, and snowmelt floods. The relative frequency of these types changes with the flood magnitude.

Smith et al., 2018 analyzed unusual floods by means of the upper tail ratio and identified the vicinity to mountains and intense thunderstorms as driving factors. This supports the incorporation of process knowledge in flood frequency analysis (Merz & Blöschl, 2003). For instance, altered snow-melt processes and increasing rain-fed runoff are of particular responsibility for changing flood features in the European Alps, next to human-induced changes in the river network (Rottler et al., 2019, 2020). Yet, the processes we are able to identify and quantify strongly depend on the kind and the resolution of the data sets at hand, also shown by the following case study.

2.1 | Case study: The flash flood of Braunsbach

The case study illustrates the dependence of processes on data resolution and the consequences for the flood hazard estimation. The flash flood event occurred on May 29, 2016 in a hilly agricultural 6 km^2-sized catchment in Southwest Germany. The event was characterized by local, short, and extreme rainfall intensities, extreme rates of catchment runoff, discharge rates, and large rocky and woody debris in the local creek. The municipality Braunsbach at the outlet of this catchment was flooded and severely damaged. The event was analyzed and reported referring the hydro-meteorological conditions by Bronstert et al. (2017, 2018), the geomorphological consequences by Ozturk et al. (2018), and regarding damage in the municipality by Laudan et al. (2017) and Vogel et al. (2017). First, we analyze the meteorological conditions followed by an analysis of the runoff processes.

A nearby rainfall station, providing daily rainfall values since 1931, measured 105 mm for that day. Based on the observed data before this event and GEV-distribution-based extreme values statistics, the exceedance probability of this 24-h-value was estimated below 0.1%, that is, a return period of >1000 years. However, including the observation from May 29, 2016 into the extreme value statistics yields a return period of about 100 years. These differing results illustrate the sensitivity of extreme value statistics to observation record duration. However, a sub-daily analysis is required for a rainfall–runoff analysis, because its convective nature also implies a high spatio-temporal variability of rainfall and runoff. Bronstert et al. (2018) showed that the rainfall event was much shorter than a day. To cope with the inherent high spatio-temporal heterogeneity, all nearby rainfall stations and rainfall radar data-products provided by the German Weather Service (DWD) were analyzed using tools provided by Heistermann et al. (2013, 2015), yielding a consistent and plausible estimate of the extreme rainfall amount: around 131 mm fell over the 6.3 km^2 catchment in just 2 h (16:00–18:00 UTC), while the main rainfall fell within only 70 min.

This extreme rainfall intensity (max 1 h-value: 108 mm/h) resulted in the prevalent infiltration of excess water in the agricultural area, followed by wide-spread inundation, surface flow, and soil erosion. A so-called forensic hydrologic analysis yielded a peak discharge estimate of ~120 m^3/s in the local creek (estimates ranging between 90 and 135 m^3/s, depending on four different approaches, see Bronstert et al., 2018 for details). Figure 2 shows the comparison of this value with the local flood design estimates (FDE), which are suggested in the online-guidelines of the State authorities (LUBW, 2015), based on an empirical regionalization of previously measured flood events. This regionalization method establishes an empirical relationship between the measured peak runoff rates at the federal state gauges and landscape parameters (e.g., geology, slope, soil types, land use, catchment size). This method does not comprise measured rainfall or discharge events of neither such a rather small spatial scale nor such high recurrence interval. Consequently, these guidelines yield the 10-year

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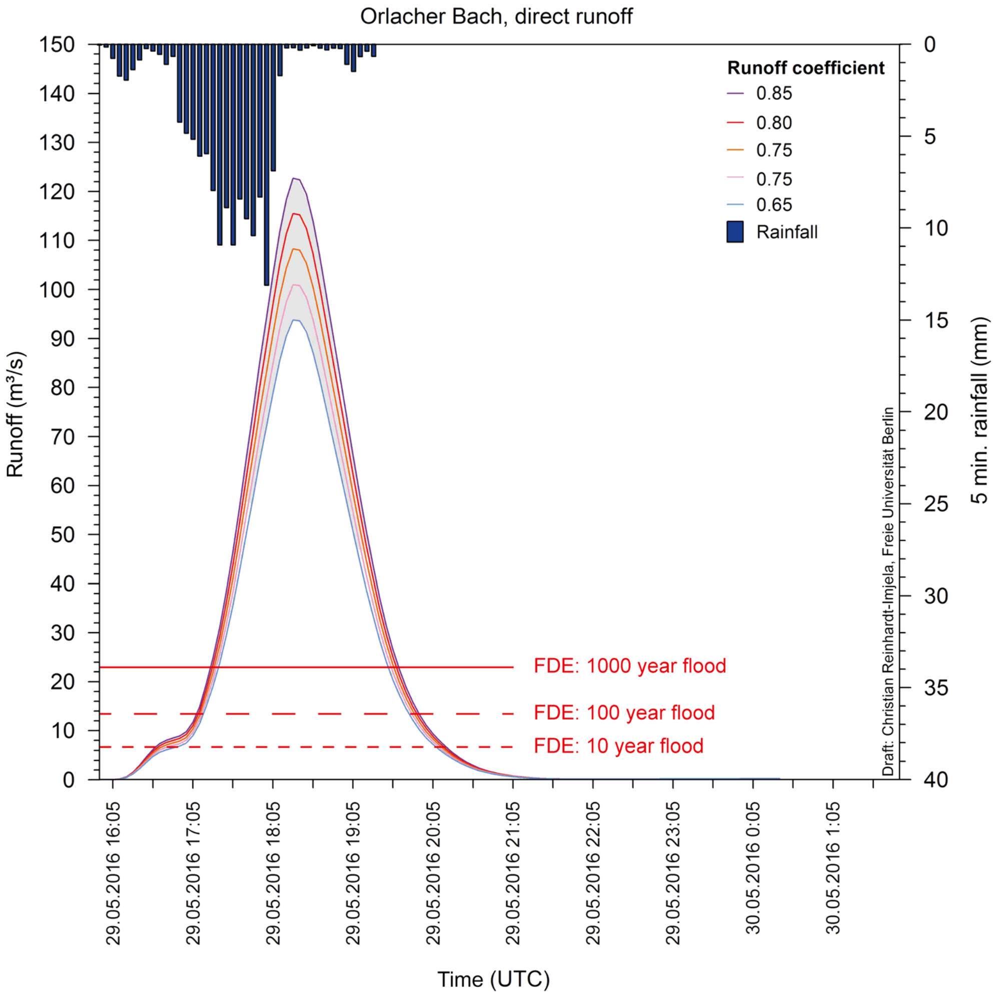

FIGURE 2 Flood hydrographs for the local creek in Braunsbach (resulting from a forensic approach based on distributed rainfall-runoff modeling) for runoff coefficients varying between 0.65 and 0.85. The local flood design estimates (FDE) for the 10-year, 100-year, and 1000-year floods are also shown (Adapted from Bronstert et al., 2018).

flood discharge values with 6 m^3/s, the 100-year flood with 12.6 m^3/s, and the 1000-year flood with 22.4 m^3/s, respectively, for the creek under study (see Figure 2). Thus, the 100-year (1000-year) FDE-value is 8–10 times (ca., 5 times) lower than the values resulting from the forensic approach. This illustrates that the peak discharge of this event was "out of range" compared with the values obtained from the empirical peak discharge regionalization method. The discrepancies between the design values and the observation estimates of the extreme event show the strong dependence of design values on the underlying method and the available database. For localized short events, current databases have only limited validity for extreme rainfall–runoff conditions. These databases can be enhanced by the inclusion of historical events, also from catchments with similar hydroclimatological conditions. For instance, in Braunsbach an event of a neighboring catchment in 1927 (Vogel et al., 2017) could be used.

This case study demonstrates the challenges in estimating the probability and magnitude of local and highly dynamic events. Conventional regionalization approaches based only on direct measurement data from the relatively coarse observation networks of rainfall stations and river discharge gauges may not provide a meaningful hazard estimation in such cases. Existing observation networks may miss a high number of such small scale, spatially limited events. The analysis of radar observations over a larger domain could support the estimation of extreme rainfall characteristics (Saltikoff et al., 2019). Detailed post-event studies of extreme events in ungauged catchments could complement observations from rainfall or discharge gauges to better understand space–time dynamics and occurrence probabilities of such extreme events, as demonstrated, for example, by Kunz et al. (2013), Fuentes-Andino et al. (2017), or Bronstert et al. (2018). Paleo-flood or paleo-geomorphological proxy data of historical events could extend the record length (Halbert et al., 2016). Improvements in data acquisition and understanding of the process mechanisms of extreme events are required for a more reliable estimation of their occurrence probability as well as the associated risk. Future flood risk assessments in similar catchments should therefore especially consider key questions 1 and 3.

3 | HYDRAULICS

Hydrodynamic models convert river discharges into inundation characteristics. The literature offers a wide range of options of how to consider inundation processes. The spectrum ranges from the numerical simulation of complex processes, including for example dike breaches, transport of debris, and intricate urban flow situations, using numerical solvers (1D–3D) to the estimation of flood extent using simple GIS analyses. In terms of space–time dynamics, the spectrum extends from local, highly resolved ($dx \sim 5$ m) to global ($dx \sim 1$ km) resolution, and from highly resolved dynamics ($dt \sim$ sec) to stationary approaches ignoring the event dynamics. Inundation characteristics that are typically quantified and further used as input in risk models are inundation extent and water depths. In some cases, additional hazard characteristics are estimated, in particular flow velocity, inundation duration, or the rate at which the water rises (De Moel et al., 2009).

Most flood risk assessments apply hydrodynamic simulation, typically employing 1D, 2D, or 1D/2D schematizations. The 2D approaches are generally needed to reproduce the complex flow paths generated in urban environments (Costabile et al., 2020). Thanks to modeling advances and the increase in computational resources and data availability, it is now feasible to perform 2D simulations at very high resolutions (even decimeters) (de Almeida et al., 2018; Sanders & Schubert, 2019). Flexible meshes are increasingly used, allowing a fine spatial resolution in areas that show highly dynamic flow situations (Savant et al., 2019). Complex situations can be modeled, for example, levee breaches (Dazzi et al., 2019) or due to the interaction of wood, eventually entering the stream pulled out by landslides, bank erosion and debris flow, and the existing man-made structures in urbanized areas, such as bridge piers (Persi et al., 2018).

The 2D inundation simulation is typically based on the shallow water equations, but demand for computationally efficiency has led to the development of simplified approaches. Two widespread simplifications are "zero inertial" or "diffusive wave" approximation and "local inertial approximation." Another widely used family in urban areas is based on the shallow water equations with porosity—and different porosity approaches (Costabile et al., 2020). During the last decade global hydrodynamic river routing models have increasingly been developed and implemented, for instance, for continental or global flood risk assessments. An example is CaMa-Flood (Catchment-based Macro-scale Floodplain model; Yamazaki et al., 2013) which uses simplified shallow water equations to represent river routing and floodplain inundation, typically based on grid cells with spatial resolution of a few kilometers to tens of kilometers (e.g., Wing et al., 2020).

A considerable amount of studies compare the performance of different simulation approaches, including the sensitivity to space–time resolution, using benchmark tests and real-world flood events. Examples are Hunter et al. (2008), Apel et al. (2009), Fewtrell et al. (2011), Neal et al. (2012), Neelz and Pender (2013), Falter et al. (2013), Kvočka et al. (2015), Papaioannou et al. (2016), Afshari et al. (2018), and Costabile et al. (2020).

There is no general consensus of how detailed an inundation model should be to provide reasonable results (Costabile et al., 2020). This is not surprising as the choice of the level of detail depends on the context of the study, for example, purpose and aim, available resources, and expertise. For instance, 2D approaches are needed to develop emergency activities based on logistic operations and road accessibility (Arrighi et al., 2019). Besides the modeling approach the consideration of structures and infrastructures in the model set-up could deserve more attention and is thus the focus of our case study.

3.1 | Case study: How much do dikes matter in risk estimations?

Here we present a case study on the consideration of embankments in risk analyses on the mesoscale in Lower Saxony, a federal state in Germany. Flood hazard maps produced according to the European Floods Directive (2007/60/EC; EC, 2007) are publicly available as GIS vector data sets. These official 100-year flood hazard maps (HWG) were compared with the 100-year flood scenario calculated by the model LISFLOOD and provided by the European Joint Research Centre in 2013 as raster data set with a grid cell size of 100 × 100 m (Adelphi et al., 2015), which, however, neglected embankments. For the comparison and the subsequent loss modeling the spatial resolution of the hazard maps was harmonized to a common grid cell size. For this, the HWG data was converted to a raster file with a resolution of 100 × 100 m. To ensure that the respective grids of the two maps overlapped, the grid conversion of the HWG map aligned the grids with those of the LISFLOOD map. In addition, the water levels were classified in the same way, that is, <0.5 m; 0.5–1 m; 1–2 m; 2–4 m; and >4 m according to the official flood hazard maps.

For the damage estimation, the Flood Loss Estimation Model for the private housing sector (FLEMO-ps; Thieken et al., 2008) was adapted to the water level classes mentioned above, that is, new mean damage ratios were empirically derived for the new water level classes. In comparison to Thieken et al. (2008), who solely relied on data from the 2002-flood, a much broader empirical data set was used containing more than 2000 damage cases in the residential sector from six river floods that occurred in Germany between 2002 and 2013 (see Thieken et al., 2017). In addition, the asset map of Kleist et al. (2006) was updated to the building stock of 2011 and adjusted to prices of 2015 by a building price index. Asset values were spatially allocated as shown by Thieken et al. (2006) using CORINE land cover data. The loss model was applied to both hazard maps.

The comparison revealed that the official 100-year flood hazard maps inundated areas of 1596 km^2 affecting 343 municipalities, while the comparable LISFLOOD scenario delivered 2485 km^2 (i.e., 156%) affecting 400 municipalities. Based on the official 100-year flood hazard maps the estimated damage amounted to €1023 million in Lower Saxony, while LISFLOOD resulted in €2065 million, that is, 202%. It should be noted, however, that the differences between the two hazard maps are not consistent in all of Lower Saxony. Figure 3 reveals that damage estimates based on LISFLOOD are lower in comparison to the official hazard maps in 104 municipalities, which are mainly located in upstream areas. In 304 municipalities, the damage based on the LISFLOOD flood hazard map exceeded the damage estimated with the official hazard maps, on average by €2.4 million. This pattern illustrates that in lowland river systems embankments play a key role for the inundation and associated risk estimates.

This case study illustrates that the consideration or negligence of embankments considerably affects the estimated extent of inundated areas (by a factor of 1.5 in this case) and subsequent loss estimates (by a factor of 2). Depending on the decision problem at hand it has to be decided whether such big differences are still acceptable when applying a coarse hydraulic model on the regional scale. This refers especially to key question 1. The case study illustrates that particularly along lowland rivers, embankments must not be ignored in hydraulic modeling. However, accurate data on embankments are often

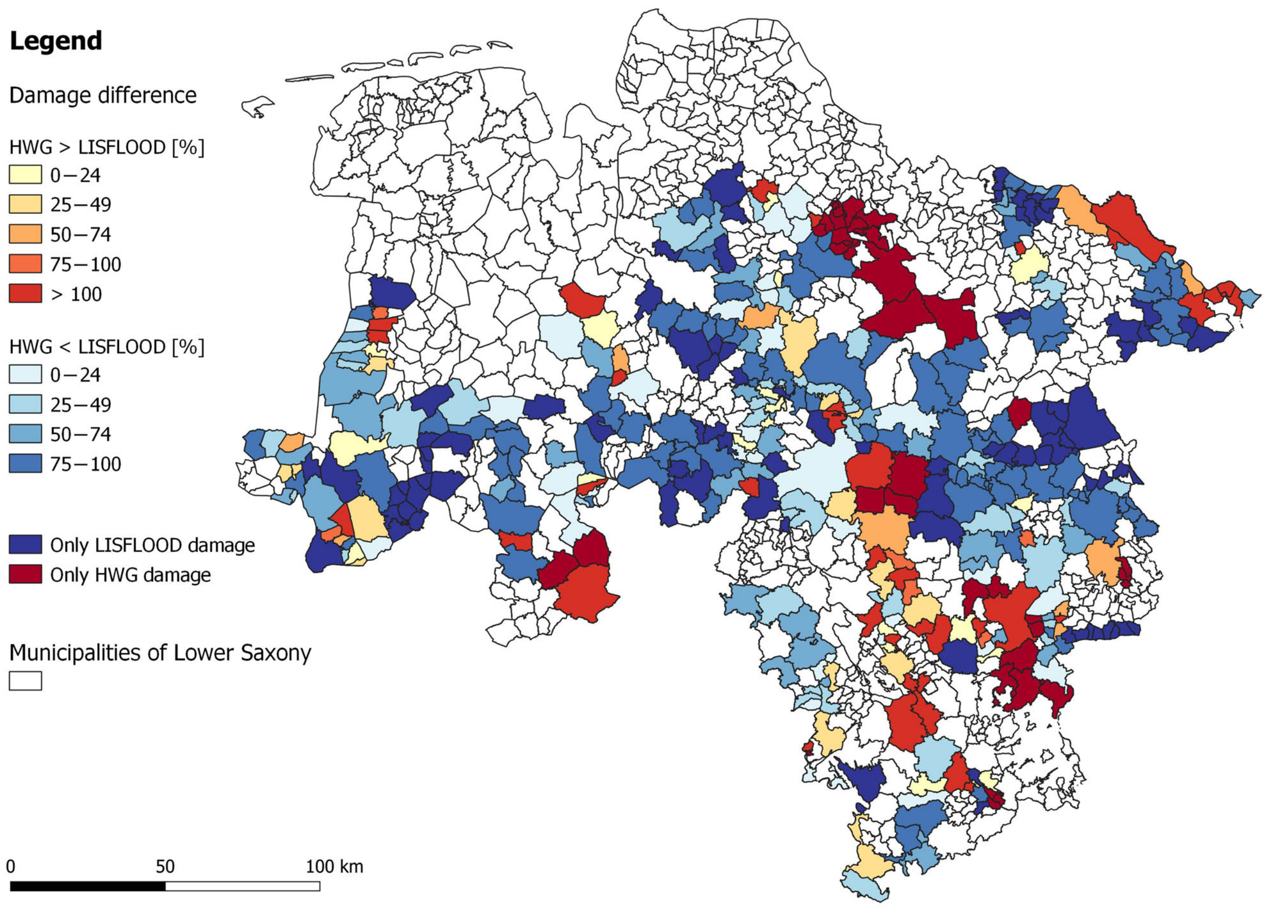

FIGURE 3 Differences of damage estimates in municipalities in Lower Saxony, Germany based on flood maps provided by the European Joint Research Centre (JRC; computed with LISFLOOD without embankments) and the official hazard maps HWG, which are publicly available and consider embankments). Areas in red indicate higher damage estimates based on LISFLOOD, while areas in green indicate higher damage estimates with HWG flood maps.

unavailable. Hence, in doubt, whether efforts should be increased to gather data on dike locations and heights or better hydraulic models, dikes seem to play a more important role, particularly for scenarios of frequent floods up to the design level of the dikes (see Merz & Thieken, 2009). This is underlined by findings that these frequent scenarios influence the expected annual damage, which is the most used risk metric, more than extreme scenarios (Merz et al., 2009; Merz & Thieken, 2004).

4 | EXPOSURE DATA SETS

The estimation of the elements and their asset values exposed to the hazard is the next essential step in risk assessments. Typically, data sets and methods with different levels of detail are used at different spatial scales (de Moel et al., 2015). Traditionally, land use data is used at mesoscale (Kreibich et al., 2016), while gridded values of the gross domestic product (GDP) can be used at the global scale (Ward et al., 2013). Recent advancements in exposure data arising from data sets like the OpenStreetMap (OSM) (Pittore et al., 2017; Wieland & Pittore, 2017) enable object-based approaches to estimate flood damage to buildings (Sieg, Vogel, et al., 2019) or infrastructure (Bubeck et al., 2019; Kellermann et al., 2016) across spatial scales. These data sets can also be used to assess the risk of multiple hazards to infrastructure at the global scale (Koks et al., 2019) and buildings at the local scale (Prahl et al., 2016).

One limitation of the newly available data sets is the accuracy of the objects (e.g., building footprints or roads) as well as their completeness. The local geometric accuracy of roads can be over 90% compared with reference data sets (Chehreghan & Ali Abbaspour, 2018), while the completeness of roads is over 80% globally (Barrington-Leigh & Millard-Ball, 2017). Building footprints showed high similarities to authority data, although with a lower level of detail (Fan et al., 2014). Regional studies on the completeness of buildings in the last years report a coverage of 25% in regions of Germany in 2011 and 57% in regions of Italy in 2017 (Brovelli & Zamboni, 2018; Hecht et al., 2013). In general, the level of completeness of roads and buildings varies strongly from region to region (Barrington-Leigh & Millard-Ball, 2017; Brovelli & Zamboni, 2018; Hecht et al., 2013), but was observed to increase over the last years (Chehreghan & Ali Abbaspour, 2018). Hence, the accuracy and completeness of the data sets should be considered and checked before applications in flood risk estimations to avoid underestimations of exposed objects.

Next to a consistent mapping of exposed objects, the consistent estimation of exposed asset values is crucial for risk assessments. Using land use datasets requires a disaggregation of asset values from a larger scale (e.g., country-wide values) to areas with a specific use (e.g., Chen et al., 2004; Kleist et al., 2006). Wünsch et al. (2009) illustrated that it is more beneficial to invest in higher-resolved land use data than in more sophisticated disaggregation methods. A study comparing different methods of building asset estimation in Switzerland suggests the use of methods based on individual building data rather than land use data (Röthlisberger et al., 2018). In this case, building asset values need to be calculated per object. This can also be done by disaggregating values to building footprints (Wu et al., 2019). Paprotny et al. (2020) provide a European-wide database for asset values of private households. Company assets can be disaggregated by statistics on employees and asset values of companies on larger scales (Sieg, Vogel, et al., 2019). Consequently, it has become feasible to use highly resolved spatial exposure data at various spatial scales promising a more accurate flood risk estimation. The following case study quantifies the differences between two exposure data sets with different degrees of detail.

4.1 | Case study: Differences between exposure data sets in Germany

To illustrate the difference between exposure data sets we compare asset values of companies exposed to a 100-year flood event in Germany based on OpenStreetMap data and land use based Basic European Asset Map (BEAM) (Mueller et al., 2013). The BEAM data set provides monetary asset values per area units. The data set is derived by socio-economic statistics from the EUROSTAT database and enhanced CORINE land use data. The CORINE land use data is enhanced with data from the Urban Atlas (2021) (a Copernicus land monitoring service) which increases the spatial resolution in urban areas. In addition, linear infrastructure was added.

For this analysis, we used OSM objects and BEAM areas with a predominant use of commercial or industrial activities and public services to estimate assets for companies and OSM objects and BEAM areas with a predominant use for residential purposes to represent private households. The flood-prone areas are taken from the flood hazard map for Europe with a 100-year return period (Dottori et al., 2016). Both data sets are spatially intersected with the flood-prone areas and only asset values within these areas are considered as exposed. Net asset values in the exposed BEAM areas categorized as buildings and inventory assets per square meter of industry and service are taken for the companies and those categorized as building and content assets per square meter of private households are taken for the residential asset values. Buildings located within the flooded area and whose type is related to companies (e.g., commercial, service, or retail) or residential are taken from the OSM data sets. The asset values of buildings and equipment of the companies is estimated based on official statistics from the national accounts (VGR des Bundes) and the German Federal Statistical Office. Content asset values of private households are taken from Paprotny et al. (2020), The assets for OSM data are estimated with the unit scaling method following the approach of Sieg and Thieken (2022). These values are compared with the land use based Basic European Asset Map (BEAM as of 2012) (Mueller et al., 2013). Both values are given as net asset values.

Figure 4 shows a comparison of the exposed asset values for companies and residential objects per federal state in Germany. The factor indicates how much higher the asset values estimated by the respective data set are in comparison to the other data set. The estimation of the assets of the OSM data set is based on a sampling scheme resulting in a distribution of asset values. The 10th, 50th, and 90th percentile of the distributions are indicated by different saturation levels of the black lines.

The estimated assets and areas of OSM and BEAM show differences up to a factor of 15 for companies considering the median value of estimated assets for OSM data only and up to a factor of 2 for assets of residential objects. The exposed assets of companies derived from the BEAM data sets are larger in all federal states. Asset values of residential objects show less differences between the two data sets with factors between one and two. Yet, the BEAM data set tends to estimate the asset values higher than the OSM data sets. For the whole of Germany the absolute numbers of net asset values exposed to a (static) 100-year flood are calculated for the BEAM data set to around 366 billion Euro for companies and 191 billion Euro for residential areas. OSM data showed exposed asset values of around 92 billion Euro for companies and 176 billion Euro for residential objects. Exposed company assets from the BEAM are therefore 3.95 times higher compared with the company's assets determined by means of the OSM data. Assets from private households are estimated 1.08 times higher with BEAM than with OSM data. Consequently, the choice of exposure data sets with different spatial resolutions and hence different asset estimation methods does affect the estimated exposed areas as well as the exposed asset values. These differences strongly propagate to risk and damage estimates. This effect varies between different sectors (e.g., the commercial sector and the residential sector). In the case of the federal state Lower Saxony, for example, the choice of the exposure data set has, with a factor of 3.8 for companies and 1.3 for private households, about the same influence on the damage estimates

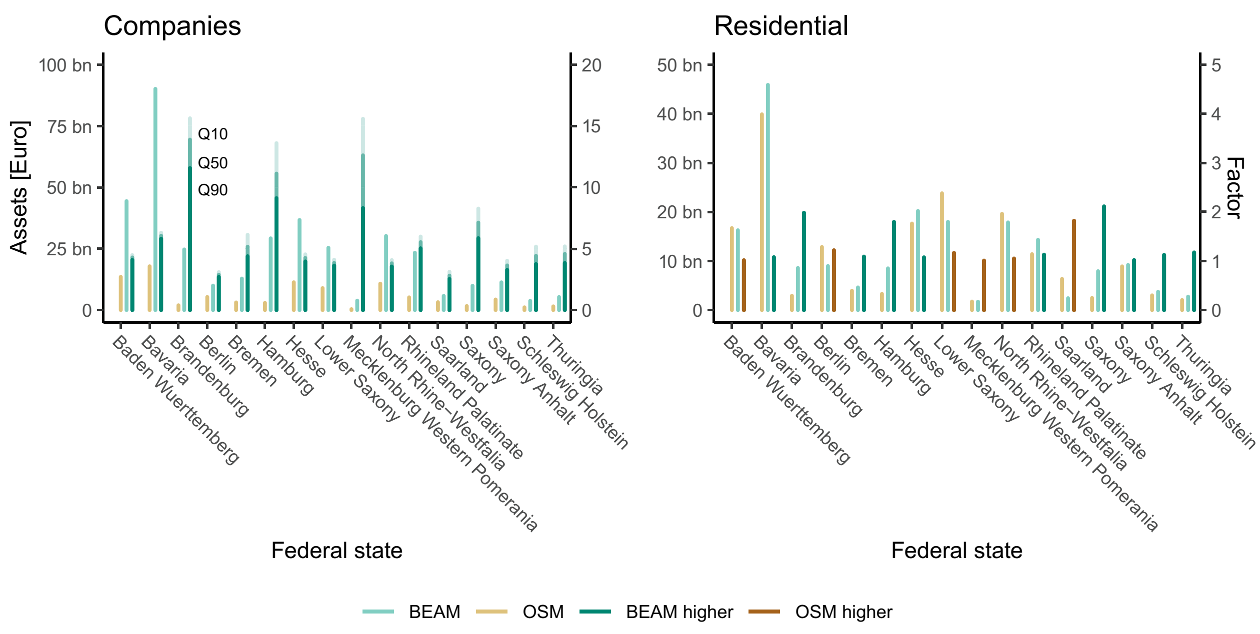

FIGURE 4 Comparison of exposed net asset values for companies (areas which are predominately used for commercial or industrial activities and public services) and or residential objects to a 100-year flood event per federal state in Germany calculated with OpenStreetMap (OSM) and the Basic European Asset Map (BEAM) data sets. The factors show how much higher the estimated exposed net asset values of one data set are compared with the other.

as the consideration or negligence of embankments, which resulted in a factor of 2 (Section 3.1).

In conclusion, the analysis showed that the use of exposure data sets with different levels of detail results in very different estimates of assets and areas exposed to a 100-year flood event. This finding is transferable to regions with a similar degree of completeness of the OSM data. The choice can therefore have a tremendous impact on the estimation of risk. The impact is comparable to the consideration of dike lines. It can be assumed that the OSM data is at least for the estimation of exposed areas more accurate due to the higher spatial resolution. The estimation of the assets plays an important role, too. However, the effects of exposure mapping and asset estimation on flood risk assessments are rarely quantified. General recommendations considering the choice of exposure data and asset estimation methods for the use at different spatial scales and various purposes (e.g., future flood risk assessments or near-real time flood damage estimation) cannot yet be made. This example shows that key questions 1 and 3 need to be answered for exposure data sets, too.

5 | DAMAGE ESTIMATION AND PROCESSES

The description of damage processes by flood loss estimation models ranges from single-variable depth-damage functions to probabilistic multivariable models (de Moel et al., 2015; Gerl et al., 2016; Merz et al., 2010). Depth-damage functions only use water depth to determine flood damage, and are individually set up for various objects or land-use units commonly separated according to their use or sector (Natho & Thieken, 2018; Penning-Rowsell et al., 2013). Multivariable damage models use impact and resistance variables to estimate flood damage and are also commonly developed separately for different sectors like manufacturing or services (Kreibich et al., 2010; Sieg et al., 2017).

The observation that damage processes and consequently damage driving factors differ between sectors and building uses goes back to Grigg and Helweg (1975), and is the basis for the standard approach to develop separate flood damage models for each sector (e.g., Molinari et al., 2020). The emergence of detailed empirical data sets and sophisticated statistical data mining approaches over the last decade allow us to identify the main drivers of flood damage (Merz et al., 2013; Rözer et al., 2019; Sieg et al., 2017; Vogel et al., 2018). Besides the most important variable, that is, water depth, also return period, contamination, inundation duration, flow velocity, different indicators for building size, and precautionary measures were identified as important variables determining flood damage of residential buildings (Merz et al., 2013; Mohor et al., 2020; Vogel et al., 2018) and respective multivariable damage models for residential buildings have been developed (Kreibich et al., 2017; Schröter et al., 2014).

For companies, damage processes vary across economic sectors and assets like buildings, equipment, and goods and stock (Sieg et al., 2017). However, generally, again water depth is the most important damage driver; in addition, contamination, company size, and precautionary measures are important (Sieg et al., 2017). Accordingly, multivariable loss models for companies were developed (Kreibich et al., 2010; Schoppa et al., 2020; Sieg, Vogel, et al., 2019; Sultana et al., 2018). In contrast, damage processes, and consequently damage models, are quite different for agricultural crops, for which the most important damage drivers are the crop type, flood timing during the year, and with less importance the inundation duration, whereas other parameters such as water depth and flow velocities play a minor role (e.g., Citeau, 2003; Dutta et al., 2003; Förster et al., 2008).

New property level datasets collected after flood events also allowed us to investigate and quantify the mitigation effect of private precautionary measures in detail (Hudson et al., 2014; Kreibich et al., 2005; Poussin et al., 2015). However, only few flood damage models take precautionary measures into account as a damage determining variable, although doing so supports temporally dynamic flood damage and risk modeling and enables the evaluation of integrated flood risk management. Early examples of multivariable models considering precautionary measures for private households and companies are the FLEMOps and FLEMOcs models (Kreibich et al., 2010; Thieken et al., 2008). Other multivariable models followed, for example, tree-based models (Carisi et al., 2018; Hasanzadeh Nafari et al., 2016; Kreibich et al., 2017) and Bayesian network-based models (Lüdtke et al., 2019; Paprotny et al., 2020; Vogel et al., 2012; Wagenaar et al., 2018). However, tree-based models are not well suited to capture differences in precaution, while FLEMOps and the Bayesian network-based model BN-FLEMO are very well capable of capturing differences in precaution (Sairam et al., 2019).

Flood damage processes also differ between different flood types, like riverine, dyke breach, groundwater, pluvial or flash floods, which show significantly different hazard characteristics (Kreibich & Dimitrova, 2010; Laudan et al., 2017; Mohor et al., 2020). Thus, specific models were developed separately for different flood types, for example, for groundwater floods (Kreibich & Thieken, 2008), coastal floods (Naulin et al., 2019; Suppasri et al., 2019) or pluvial floods (Blumenthal & Nyberg, 2019; Spekkers et al., 2014; Van Ootegem

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et al., 2015, 2018). In contradiction to this notion a probabilistic residential loss model for different flood types was suggested for Europe recently (Paprotny et al., 2020). However, data-driven studies, for example, by Mohor et al. (2020, 2021), illustrate that flood-type specific models are more reliable than models that try to capture all flood types.

Availability of detailed multidimensional datasets needed for multivariable damage models is still scarce in many regions limiting their widespread application. In addition, overfitting can become a problem, when multivariable models trained only with data from one region are transferred to another. For the example of a transfer of damage functions between two regions in Italy, Amadio et al. (2019) show that simple expert-based damage functions can outperform sophisticated multivariable damage models if their transferability is not carefully evaluated. Bayesian approaches in combination with heterogeneous empirical data sets have been used to improve the spatial and temporal transferability of empirical damage functions by accounting for the full parameter distributions estimated from the data in one region to inform the application in another region (Wagenaar et al., 2018). The use of probabilistic approaches with different degrees of complexity is also subject of the following case study.

5.1 | Case study: Pluvial flood loss modeling

This case study uses a fully probabilistic modeling approach for a consistent quantification of uncertainties associated with pluvial flood loss estimation for residential buildings (Rözer et al., 2019). Here the focus is on investigating differently detailed damage process descriptions, and how these influence the uncertainty associated with a pluvial flood loss estimation.

A Bayesian zero-inflated beta regression, a Bayesian parametric model based on a Gaussian response distribution and a non-parametric model based on the Random Forest algorithm are used to predict the relative loss to a building by pluvial flooding. The three model types are fitted as uni- and multivariable models, so that both, the effect of model type as well as the effect of additional predictor variables on the predictive performance are investigated. The univariable models use water depth as the only predictor reflecting the standard in flood loss estimation (see above). All multivariable models use the same predictors, namely water depth, inundation duration, contamination (yes/no), multifamily home (yes/no), household size, and knowledge about flood hazard of the respective household. The additional predictors have been selected from a set of 44 potentially loss-influencing variables using the average rank of variable importance measures from an ensemble of four different supervised learning algorithms (linear penalized regression and non-linear regression tree models). This approach ensures a robust selection of the most important loss-influencing variables by minimizing the bias from the selection of a specific class of models (e.g., linear models). Water depth was consistently identified as the most important predictor, followed by inundation duration. This is followed by household size, knowledge of flood hazard, contamination, and multifamily home, which have a high average rank but larger variation in ranks between the four different models, indicating a lower predictive power depending on the variable importance measure.

All six models are trained and validated with a local training data set based on data collected after pluvial flood events in Germany (Rözer et al., 2016). The Gaussian model is fit using Bayesian ordinary least square (OLS) regression with weakly informative priors both in the uni- and multivariable setting. The RandomForest model is fit using the original RandomForest algorithm by Breiman (2001) with 2000 independent trees. For the Beta model a Bayesian logistic regression is fit to determine the probability of no damage (zero-inflation) followed by Bayesian beta regression with a beta-distributed response function. The models are then used for a probabilistic estimate of residential building losses of over 304,000 buildings in Harris County, including the city of Houston (Texas, USA), due to extreme pluvial flooding during Hurricane Harvey at the end of August 2017.

The investigation reveals significant differences in the performance of the models depending on the use of additional predictors, the choice of response distribution, the ability of the model to account for zero-loss cases, and the spatial scale of the analysis, when compared against reported damage (Figure 5). The uncertainty of pluvial flood loss modeling on building level can be significantly reduced by 47% when using a zero-inflated beta distribution (Beta) instead of normal response distributions without sacrificing the reliability (Rözer et al., 2019). Using water depth as the only predictor results in an underestimate of the prediction uncertainties, meaning a low accuracy of loss estimates. A combination of additional predictor variables and zero-inflated Beta regression models improve the loss estimation in two ways, (a) by increasing the accuracy of the loss prediction through a more realistic representation of uncertainties when aggregating estimates and (b) by improving the precision through a better detection of cases where inundation affected the building but did not cause any building loss. This indicates that the ability of households to prevent direct losses should be included in loss models.

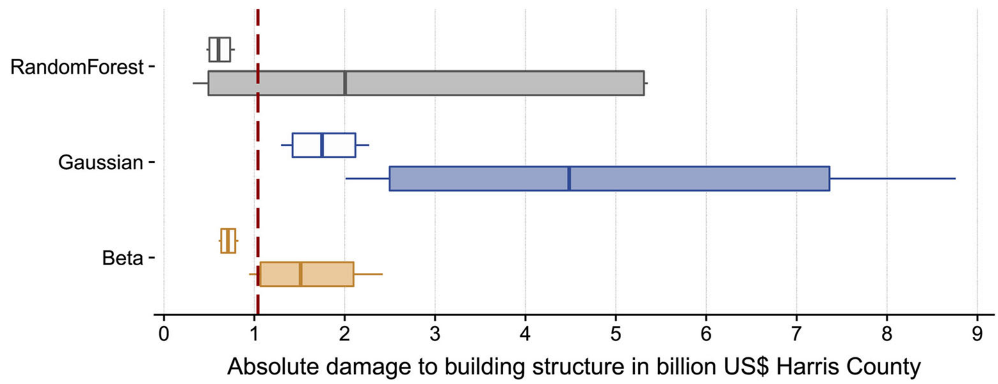

FIGURE 5 Absolute direct building structure damage estimates in billion US$ for three different model types (RandomForest, Gaussian, and Beta) in their univariable (hollow; water depth only) and multivariable (solid) versions. Bars indicate the median absolute loss, boxes the 90%, and whiskers the 98% interval of the absolute direct building loss for Harris County, Texas. The red dashed line represents the officially reported absolute building structure damage based on data from the US Federal Emergency Management Agency Housing Assistance Program (FEMA) (Adapted from Rözer et al., 2019).

Commonly specific loss models for different sectors and flood types are developed to map the different damage processes. Only few flood damage models take resistance aspects like private precaution or building material into account as a loss-determining variable. However, doing so improves the description of the damage processes. Probabilistic multivariable loss models are improving the description of the stochastic damage processes and inherently provide quantitative information on uncertainty associated with both the random heterogeneity of input data and the model structure. This facilitates better risk communication and informed decision-making. Regarding key question 1, the damage models should be chosen according to the identified relevant processes for the risk assessment.

6 | CAPACITY AND ADAPTATION

In recent international terminology, disaster risk is defined "[...] as a function of hazard, exposure, vulnerability, and capacity" (UNDRR, 2021). While hazard, exposure, and vulnerability are frequently considered in risk estimates as highlighted in the previous sections, it is unclear how to quantitatively consider capacities. High capacities decrease risk and therefore counteract hazard, exposure, and/or vulnerability as was recently outlined by Simpson et al. (2021) in the context of climate change. This interaction challenges the conceptual model setup.

Capacities can be qualitatively addressed, for example, by the capital approach and have as such been assessed within communities (Keating et al., 2017) or a large company like the Austrian Railways (Otto et al., 2019). Such studies highlight strengths and weaknesses of the risk management system in place, but fail to quantify how much flood risk is reduced by certain measures or policy interventions. Therefore, different risk management strategies (which require certain capacities) on how to adapt to flooding and to reduce the risk, are commonly considered by (static) scenarios (e.g., Molinari et al., 2021; Thieken, Cammerer, et al., 2016). Scenarios are used to assess costs and benefits of specific risk reduction strategies and measures to find cost-effective solutions. The effect of the measure itself is integrated in the assessment of either hazard (e.g., when building new dikes), exposure (e.g., when strengthening spatial planning or zoning policies), or vulnerability (e.g., by altering stage-damage curves or more sophisticated loss models). For example, the damage reduction by wet flood-proofing amounts to 35%–50% and to 22%–65% for dry flood-proofing (Kreibich et al., 2015). In this context wet flood-proofing mitigates damage although water has entered the building, for example, by flood-adapted use or materials, while dry flood-proofing aims at preventing water entry, for example, by sealed walls or water barriers; property-level adaptation is used as an umbrella term. Typical costs of measures are provided by Aerts (2018). Microscale approaches have been recommended for detailed outcomes (de Ruig et al., 2020; Molinari et al., 2021) creating evidence that the implementation of property-level flood adaptation pays off (e.g., Attems, Thaler, Genovese, & Fuchs, 2020; de Ruig et al., 2020; Kreibich, Christenberger, & Schwarze, 2011). Hence, risk communication aims at motivating flood-prone residents to take up such measures (Attems, Schlögl, Thaler, et al., 2020; Attems, Thaler, Snel, et al., 2020; Heidenreich et al., 2020).

While a cost–benefit-analysis helps to inform decisions on investments in new measures, scenario-based approaches fail to capture temporal dynamics within the system under study. These might, however, be important in the case of structural measures that are known to cause co-costs by allowing built-up areas behind the dikes that increase the overall loss in case of a dike failure (Di Baldassarre et al., 2018), while nature-based solutions create co-benefits (Dittrich et al., 2019; Kousky & Walls, 2014). Hence, the types of costs and benefits considered (over time) might change the outcome of the assessment (e.g., Fadel et al., 2018).

To better capture dynamics of flood risk and societal adaptation, socio-hydrology has emerged as a subdiscipline: several differential equations are commonly used to reflect the interactions and feedbacks between flood hazard and risk as well as societal development and adaptation (e.g., Barendrecht et al., 2019; Di Baldassarre et al., 2013). While it was shown that model calibration benefits from empirical data (Barendrecht et al., 2019), model validation is often hampered by a lack of empirical longitudinal data. This is particularly relevant for the uptake and effect of non-structural measures, such as property-level adaptation, which cannot be planned systematically. However, their uptake is increasingly demanded in flood policies (Kuhlicke, Seebauer, et al., 2020), supporting calls for considering human behavior and adaptation in quantitative risk analyses (e.g., Aerts et al., 2018). To account for interactions between flood-prone residents and other stakeholders and their interventions, agent-based models have been set up (e.g., Haer et al., 2017) allowing to simulate the effect of different policies on flood risk over time. In contrast to other socio-hydrological models, human behavior is included in more detail and based on behavioral or psychological models, of which the Protection–Motivation-Theory (PMT; Rogers, 1983) has become the most popular one since Grothmann and Reusswig (2006) applied it successfully to explain flood adaptive behavior in the city of Cologne, Germany. Coping appraisal was found to be particularly important; it consists of perceived self-efficacy, perceived response efficacy, and perceived costs of adaptation (response costs) and is enhanced by observational learning from the social environment, such as friends and neighbors (Bubeck et al., 2018) highlighting the role of social capital and norms (Bixler et al., 2021). In fact, a review (van Valkengoed & Steg, 2019) across different hazards, designs, and countries revealed that self-efficacy, response efficacy, negative affect, and descriptive norms are the best predictors for adaptive behavior, while risk perception and experience show just small to moderate effects although they are more frequently studied. However, van Valkengoed and Steg (2019) further state that the motivational factors and types of behaviors researched greatly differ across the studies calling for more harmonized items in surveys. Therefore, harmonized repeated cross-sectional surveys that have been conducted among flood-affected residents and companies in Germany since 2002 (e.g., Kienzler et al., 2015; Kreibich et al., 2005; Rözer et al., 2016; Sieg et al., 2017; Thieken et al., 2007; Thieken, Kienzler, et al., 2016) are used in the case study to highlight temporal changes in adaptive behavior and their effects on flood risk.

6.1 | Case study: Effect of property-level adaptation on risk estimates

The following case study illustrates the quantitative effects of (changing) property-level adaptation on risk estimates on the regional scale, that is, the Freestate of Saxony, Germany. Over the past 20 years, Saxony has been affected by several floods. The most severe event took place in August 2002 and caused losses of €8700 million. The event also triggered the uptake of property-level adaptation measures in Saxony as a long-term flood precaution (Kreibich, Seifert, et al., 2011). Further minor flood events occurred in 2006, 2010, and 2011, while a bigger flood followed in June 2013. Again, an increase in the uptake of property-level adaptation measures was observed in the aftermath (Kienzler et al., 2015; Thieken, Kienzler, et al., 2016). To investigate the effect of improved adaptation on the flood risk, a risk analysis on the basis of the official flood hazard maps as of 2006 was performed. The hazard maps were combined with a mesoscale inventory of residential building assets and the flood loss estimation model FLEMO, which was derived from survey data and is capable of considering effects of property-level adaptation (Thieken et al., 2008). For this study, the model was updated with empirical data from flood-affected residents surveyed about floods between 2002 and 2013 (see Thieken et al., 2017, for a description of the data). Three different scenarios in the Freestate of Saxony were considered (Figure 6).

As a reference scenario, the situation before the flood of 2002 was captured by combining the flood hazard map (of 2006) with the building characteristics of 2000 and the level of property-level adaptation before the 2002-event as retrieved from survey data on the 2002-flood (Kreibich et al., 2005; Thieken et al., 2007). In prices of 2013, this analysis resulted in an expected annual damage for all of Saxony of EUR 180 million (assuming static flood maps; see Figure 6a). In a next step, the building characteristics and assets were updated to 2013, which resulted in an overall increase in damage by 1.1% for all of Saxony (compared with the reference model) due to new and better buildings (see Figure 6b). Finally, the property-level adaptation was updated to 2013 based on survey data

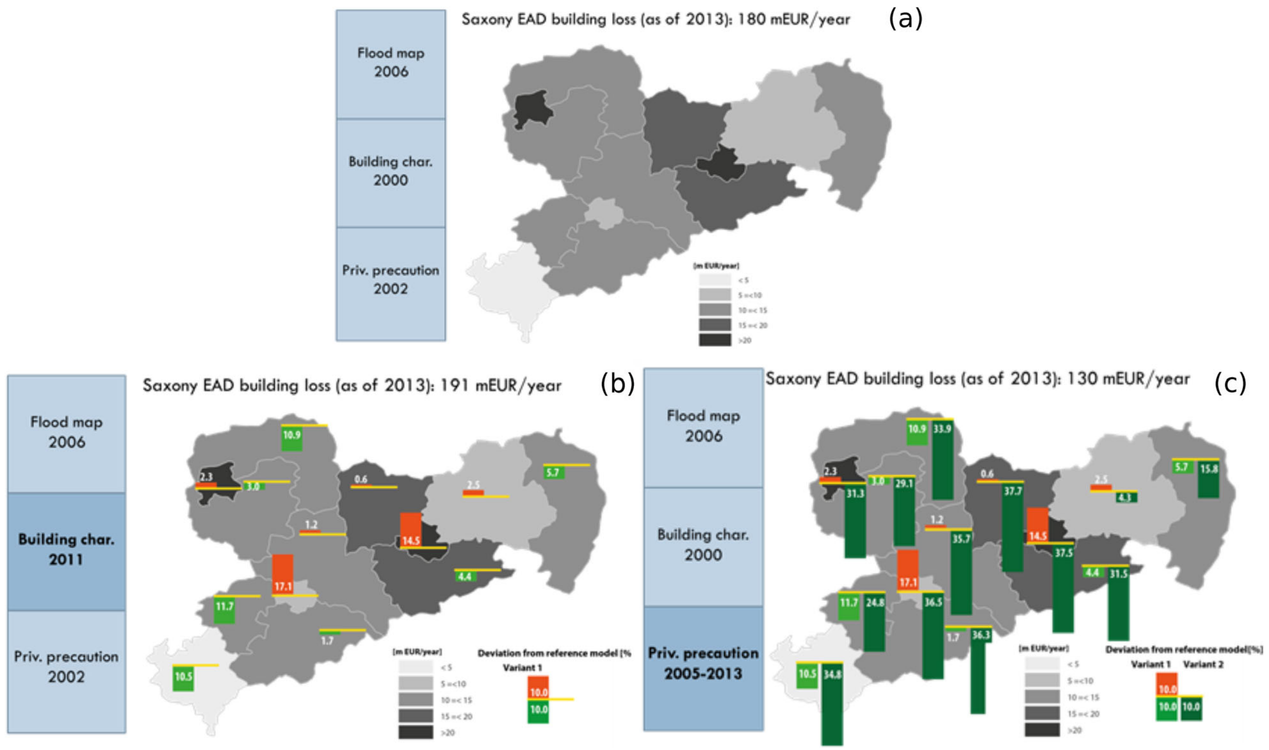

FIGURE 6 The effect of property-level adaptation on flood risk in Saxony, Germany. Expected Annual Damage by district is depicted by different shades of gray. Panel (a) shows the reference scenario with building characteristics and precautionary measures of 2000 and 2002, respectively. Panel (b) shows a scenario with building characteristics updated to the year 2011. Panel (c) shows updated private precaution to the time period 2005–2013. Percentage deviations of the damage estimates modeled with the updated versions of the data sets compared with reference scenario are given in green (lower damage estimates with updates) and red (higher damage estimates with updates).

(Kienzler et al., 2015; Thieken, Kienzler, et al., 2016), which led to a decrease in damage by 32% for all of Saxony (compared with the reference model; see Figure 6c). This estimation is in a similar order of magnitude as the average reduction of vulnerability of private households by 27% due to private precaution estimated by Sairam et al. (2019).

The modeling study illustrates the positive effect of an enhanced uptake of property-level adaptation measures on flood risk. Therefore, risk communication that motivates residents to adapt should be further supported. However, this exercise neglects that flooding also impacts mental health and people's well-being. For example, the severity of experienced flood impacts seems to be important for the motivation to implement adaptive measures (Laudan et al., 2020). Kuhlicke, Masson, et al. (2020) found an erosion of people's motivation and their resilience, when being flooded several times in a few years. To better understand temporal dynamics, panel data that capture perception, well-being, and adaptation over time are needed though their creation is challenging (Hudson et al., 2020). One of the very few longitudinal data sets in the natural hazards domain was established after the 2013-flood in Germany. It reveals that there are different types of adaptive residents (Bubeck et al., 2020). Referring to key question 2, such temporal patterns need to be considered in loss and risk models for more realistic risk estimates, particularly for projections of future flood risks.

7 | DISCUSSION

The case studies showed different systems and aspects of flood risk assessments. Although the individual case studies presented here are mostly quantitative studies, the discussion and conclusion here are more of a qualitative nature. In the following, we first want to return to the discussion of the initial three key questions posed in the introduction. Further, we want to discuss the adequate level of detail in Section 7.2 and the role of quantitative assessments in Section 7.3.

7.1 | Discussion of the key questions

All case studies dealt with at least one of the three key questions (Figure 1). The case studies showed that the use of models or data sets which incorporate more processes or spatiotemporal details can have tremendous effects on the outcome of a risk assessment. In the following we point out a few implications of the results for each key question.

7.1.1 | Which processes are relevant in the context at hand?

Processes with a higher relevance for the problem at hand should be considered with additional details. It is worthwhile to define essential processes and to add or remove the ones with substantial or negligible effects on the outcome. The case study on dike lines (Section 3), for instance demonstrates, that the consideration of embankments strongly influences damage estimates, justifying the additional resources for including embankments in the assessment. The case study on damage models (Section 5) showed that the use additional predictors enable a better description of damage processes and as such predict the damage more accurately. Assessments with a focus on damage processes should choose more complex damage models which incorporate a quantification of uncertainties or/and with a distinction of different pathways (Mohor et al., 2021). Some processes take time to implement and thus leading to an impact on a system with a temporal shift, for example, step-wise property-level adaptation on larger scales. For example, risk assessments for economic systems might also need to include indirect impacts as, for example, the disturbance of supply chains or a change of demands in course of the recovery process. These aspects are usually noticeable in the aftermath of a flood event (Willner et al., 2018). Therefore, the models which are used to quantify hazard, exposure, vulnerability and risk should be chosen based on a clear perceptual model (see e.g., Beven, 2001, on the selection of a hydrological model).

7.1.2 | Which (temporal) dynamics are relevant?

Temporal dynamics play an important role for more reliable flood risk assessments. Especially assessments supporting long-term decisions need to consider them. The useful inclusion of adaptation in the assessment of future risks requires—among other things—knowledge about the change in (property-level) adaptation over time (Section 6). Disciplines like socio-hydrology can be used to develop ideas of possible future dynamics (Di Baldassarre et al., 2013). Since some processes that show a temporal dynamic, for example, adaptive behavior of residents, are directly linked to risk management options, the use of adaptation or management scenarios must be consistently distinguished from the temporal dynamics of underlying hazard processes or scenarios of future economic developments. For example, Thieken, Cammerer, et al. (2016) distinguished a reference scenario that reflects the present situation, from a baseline scenario, which shows future (transient) behavior without adaptation, and alternative scenarios, which quantify the effects of different adaptation or management options. Analogous to this, scenarios and projections of possible future dynamics of flood generation processes including their uncertainties should be considered (Kundzewicz et al., 2018). Accordingly, risk assessments need a clear concept regarding temporal dynamics or pathways which should be explored.

7.1.3 | Which spatial and temporal resolution is needed?

In general, a risk assessment requires more detailed data the smaller their spatial extent is. The functioning of infrastructure for example depends on local features and needs locally precise inundation maps (Emanuelsson et al., 2014). The case study of Braunsbach illustrates that measurement data retrieved from relatively coarse observation networks of rainfall stations and river discharge gauges do not provide reliable hazard estimates for local flash flood events. Some data sets can have a major influence on the assessment. For instance, Section 4 showed that higher spatial resolution of exposure data results in four times smaller built-up areas and around three times lower asset values compared with data with a coarser resolution. In principle, a risk assessment that aims to prioritize different management options (within a larger region) can be coarser than an assessment that aims at identifying the best option for one specific objective (project appraisal).

7.2 | The adequate level of details

The case studies showed that risk assessments are characterized by high interactions and are influenced by many aspects. The adequate level of detail has therefore to be identified for each flood risk assessment individually. The following discussion should give some ideas on how to identify this level. For the development of environmental models Jakeman et al. (2006) point to the law of parsimony (Ockham's razor), which states that "it is vain to do with more what can be done with fewer." Applied to risk assessments this means to avoid considering all the specifics and details of every component without getting a substantial benefit for the outcome. Menger (1960) formulated the law against miserliness as a counterpart to the law of parsimony stating "it is vain to try to do with fewer what requires more." From the point of mathematics, he argued, that what is needed is a "prism" which is able to analyze mixtures and their various components instead of a mere reduction of complexity (Menger, 1960). Translated to risk assessments, this becomes relevant when looking at interplays between different components or processes (e.g., merging of flow regimes), which only get evident if all processes are described with a sufficient degree of detail. In this regard the "more" could also give room to account for the potential for surprise and unknown interrelations in risks (Merz et al., 2015). Therefore, for risk assessments it is desirable to find a "sweet spot" between the law of parsimony and the law against miserliness, so the assessments do not get overly complicated, but also include all fundamental processes.

Table 1 shows an overview of consequences and possible steps toward a "sweet spot" for flood risk assessments. Ignoring fundamental details can result in overlooked processes leading to oversimplified or false conclusions. These could lead to an over- or underestimation of risk, which in turn hampers the development of effective adaptation strategies and planning. For instance, Blöschl et al. (2020) argue that extending the database for the analysis of flood frequencies from time windows of the past decades to past centuries would lead to a better understanding of possible future flood changes and can therefore improve the adaptation capacity. Including too many details possibly leads to "wasted resources," meaning efforts (working time and financial resources) put into very detailed analysis with little gain for the results of the overall risk assessment. In this regard also data requirements of simulation efforts should be considered (Apel et al., 2008). However, to achieve a resource-efficient procedure it needs to be known which components contribute the most to enhance the degree of detail and certainty where it is needed most. In this regard it is also helpful to know about the source and type of uncertainties an assessment is prone to. Separating between aleatory uncertainty (e.g., random behavior caused by inherently variable processes) and epistemic uncertainty (originating from incomplete knowledge of a system) can support the identification of details which are able to increase the reliability (Merz & Thieken, 2005, 2009).

TABLE 1 Overview of consequences of too few or too many details considered in the process, spatial, and temporal domains as well as possible steps toward a "sweet spot" for risk assessment

Domain	Sections	Consequences of too few details	Consequences of too many details	Steps toward a sweet spot
Processes in the risk context	Sections 3 and 5	Missing impacts of processes Biased results Maladaptation in the long term Over- or underestimation of uncertainties	Sensitivity analyses, Monte-Carlo simulations, and processing of sufficiently large ensembles are hampered Interpretation of results becomes more difficult due to many captured processes Contribution of processes to overall risk is masqued Possible overfitting: redundant parameters can introduce noise	Development of a clear perceptual model/concept Evaluate the benefits of more details for the specific case/purpose Use of probabilistic models capturing the variability of the processes Use of evaluation of the results to adjust subsequent assessments
Spatial and temporal resolution of data	Sections 2 and 4	Missing identification of (changing) processes too coarse, aggregated results Over- or underestimation of risk	Wasted resources Potential introduction of noise due to more uncertain data	Use of new data and methods as well as knowing their strengths and limitations
Temporal dynamics	Sections 2 and 6	Unreliable projections of future risk Limitations to explore potential pathways of risk management	Introduction of unneeded complexity Distinction between risk and adaptation efforts (risk reduction) might become less clear	Use panel data, climate projections, and transferable models Clear definition of a reference scenario as baseline

This leads to a fourth question which needs to be considered for flood risk assessments:

7.2.1 | What are the potential consequences of too many or too little details?

It is worth striving for a balance between these extremes to enable assessments which are resource efficient and capture all essential processes at the same time. One should attempt to understand whether errors and uncertainties in the risk assessment, because of being too greedy or too wasteful, could lead to malicious consequences (Merz et al., 2015). In addition to their plausibility assumptions, models and risk estimates should be evaluated by the harmful consequences of their errors. In case of doubt, more details can potentially do less harm and even open up a room to account for surprises and unexpected interrelations. Too few details might lead to misjudgment of risk in the worst case. All these aspects strongly rely on the objective of the flood risk assessment.

Risk assessments have very different objectives and contexts. Flood risk can be assessed with a focus on ecosystems, infrastructure (transport and energy), built environment, human lives, livelihoods, or economic systems at various spatial scales. Different systems can have very different requirements to the data sets or the methods; the functioning of infrastructure for example depends on local features and needs locally precise inundation maps (Emanuelsson et al., 2014). The desired outcome can be a mere metric of risk as, for example, the expected annual damage (EAD) or it can include environmental aspects, too, like disturbed ecosystems (Meyer et al., 2009). If the objective is a timely impacts assessment the resource time might be very limited, whereas in other cases this might be the monetary, computational, or personal resources. If the assessment should support decisions within a longer timeframe it might be necessary to incorporate temporal dynamics (as pathways). Consequently, the objective and the context of risk assessments determine all the other aspects, that is the relevant processes, the required spatial and temporal resolution and (temporal) dynamics which have to be considered. Therefore, it is not possible to provide a one-size-fits-all solution on the question of the adequate level of detail.

7.3 | The need for quantitative studies

The presented four key questions offer qualitative guidance for individual flood risk assessments. Yet, clear quantitative guidance in form of thresholds defining the optimal level of details valid in different contexts cannot be given. Most case studies presented here and in the literature consider only one individual risk component mostly ignoring the interplay between the components. This kind of evaluation of the interplay between the different risk components with varying levels of detail is rare and usually limited to case studies of smaller areas (e.g., Apel et al., 2009) or using the same models with different assumptions (e.g., Metin et al., 2018; Winter et al., 2019). Yet, especially on different spatial scales the appropriate levels of detail in the single risk components could vary considerably (de Moel et al., 2015). Similar assessments are often done in the context of sensitivity analyses. However, in these analyses usually model assumptions are varied or artificial variations are introduced (e.g., de Moel et al., 2009; Metin et al., 2018; Winter et al., 2019). Comparisons between different approaches and data sets for each component with different degrees of detail are still rare (Sieg & Thieken, 2022).

Joint quantitative assessments integrating all risk components are required to reveal which details contribute most to the reliability of flood risk assessments and where resources could be spent more efficiently. More specifically, such studies could support the determination of thresholds of getting acceptable results with limited resources, hints on how to compensate the unavailability of high quality data, or identifying the optimal resolution of the data sets for the targeted flood risk assessment. However, to make these thresholds transferable it would at least be necessary to make multiple comparable assessments in a range of representative catchments, for example, in terms of the catchment size, the predominant runoff characteristics, and the population density. Increased comparability between studies and risk assessments could further enhance the meta-analysis of methods and data sets. This requires detailed documentation and discussion of the assumptions and decisions made during the assessments regarding the models, projections, data sets, and so on used. Transferable insights from other locations with better data availability or from past flood events can therefore partly compensate unavailable data sets. For example, information on exposure objects and water levels can be sampled from distributions based on official statistics or from water masks from similar events (Sieg, Schinko, et al., 2019, Sieg, Vogel, et al., 2019; Sieg & Thieken, 2022).

Ideally, such qualitative and quantitative assessments can help to anticipate flood events which appear to be surprising and make flood risk assessments more reliable. Transferred to the event of July 2021 in Germany, for instance, the consideration of historic flood events (question 2) and the link to related or consecutive processes like erosion, sediment, and debris transport and altered flood pathways, for example, due to clogging of bridges (question 3) could have supported the preparation for such an event. The goal of early warning (question 1) and its timing (question 4) could be a stronger part of the risk assessment helping to avert harm. Trajectories of rainfall, for instance, could get monitored more rigorously by means of radar data with a higher spatiotemporal resolution. Additionally, assessments could include multiple hazards (mass movements, flash floods) triggered during the event to get a clearer picture of the possible impacts and consequences. A revisited flood risk assessment for this region could benefit from the consideration of these key questions.

8 | CONCLUSION

Reliable risk assessments need to strive for a balance between greed and waste of resources needed to consider and implement the desired improvements and additional details with regard to the decision problem at hand. But do we know the adequate level of detail in flood risk assessments? Unfortunately, our current answer to this question is, that we cannot yet define this level quantitatively. For now, we can at least provide qualitative guidance toward a balance of details in individual flood risk assessments in the form of four key questions presented in this study. Methods and data sets need to be chosen deliberately in such a way that all relevant known processes are covered without being inefficient. A central requirement is to be aware of the choice and the possible influence of different levels of detail with regard to processes, spatial, and temporal resolution and to be certain about the details needed for the objective of the assessment in the given risk context.

The presented case studies of the individual risk components show that detailed considerations of specific aspects have potentially substantial effects on the flood risk estimation when considered in isolation. The quantification of the influence of different levels of detail in overarching assessments, which identifies the details that matter most for the outcomes, would support the identification of the adequate choice of detail in a given context. The implementation of such quantitative studies in various representative contexts could therefore lead to a more general definition of adequate levels of detail in flood risk assessments. A model comparison study in different areas could be a future joint effort of the flood risk research community to gain more insights into the sensitivity of risk assessment. This would not only reveal the influence of details in risk assessments, but would also hint to the next reasonable steps in flood risk research.

AUTHOR CONTRIBUTIONS

Tobias Sieg, Kristin Vogel, Heidi Kreibich, Axel Bronstert, Bruno Merz, and Annegret H. ThiekenT conceptualized the study. Tobias Sieg, Sarah Kienzler, and Viktor Rözer performed the analyses. Tobias Sieg, Heidi Kreibich, Axel Bronstert, Bruno Merz, and Annegret H. Thieken prepared the manuscript with contributions from Viktor Rözer, Kristin Vogel, and Henning Rust.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

Section 3: The data sets of the flood events in Germany from 2005 and 2013 are available via the flood damage data base HOWAS 21 (http://howas21.gfz-potsdam.de/howas21/). The flood hazard map for Lower Saxony is available at https://www.umwelt.niedersachsen.de/startseite/themen/wasser/hochwasser_amp_kustenschutz/hochwasserrisikomanagement_richtlinie/hochwassergefahren_und_hochwasserrisikokarten/hochwasserkarten-121920.html. Section 4: All official statistic data sets for the estimation of companies' assets are available from the GENESIS online data base from the German Federal Statistical Office (accession number(s) 52111-0003 and 81000-0117). All OpenStreetMap data sets are available from the OpenStreetMap online data base https://download.geofabrik.de/europe/germany.html. The Basic European Asset Map is available at https://emergency.copernicus.eu/mapping/list-of-components/EMSN024. The 100-year return period flood map is available at https://data.jrc.ec.europa.eu/collection/id-0054. Section 5: The pluvial flood inundation map for Hurricane Harvey from JBA Risk Management is available via the OASIS Hub (https://oasishub.co/dataset/surface-water-flooding-footprinthurricane-harvey-august-2017-jba). The data sets of the flood events in Germany from 2005 and 2013 are available via the flood damage data base HOWAS 21 (http://howas21.gfz-potsdam.de/howas21/). The data set from 2014 will be made available via the HOWAS21 database in June 2023. Section 6: The data sets of the flood events in Germany from 2005 and 2013 are available via the flood damage data base HOWAS 21 (http://howas21.gfz-potsdam.de/howas21/). The flood hazard map for Saxony is available at https://www.wasser.sachsen.de/hochwassergefahrenkarte-11915.html. Building asset values are available upon request.

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REFERENCES

Adelphi, PRC, & EURAC. (2015). Vulnerabilität Deutschlands gegenüber dem Klimawandel. Umweltbundesamt. Climate Change 24/2015, Dessau-Roßlau (in German).

Aerts, J. C., Botzen, W. J., Clarke, K. C., Cutter, S. L., Hall, J. W., Merz, B., Michel-Kerjan, E., Mysiak, J., Surminski, S., & Kunreuther, H. (2018). Integrating human behaviour dynamics into flood disaster risk assessment. *Nature Climate Change*, *8*, 193–199. https://doi.org/10.1038/s41558-018-0085-1

Aerts, J. C. J. H. (2018). A review of cost estimates for flood adaptation. *Water*, *10*(11), 1–33.

Afshari, S., Tavakoly, A. A., Rajib, M. A., Zheng, X., Follum, M. L., Omranian, E., & Fekete, B. M. (2018). Comparison of new generation low-complexity flood inundation mapping tools with a hydrodynamic model. *Journal of Hydrology*, *556*, 539–556. https://doi.org/10.1016/j.jhydrol.2017.11.036

Amadio, M., Scorzini, A. R., Carisi, F., Essenfelder, A. H., Domeneghetti, A., Mysiak, J., & Castellarin, A. (2019). Testing empirical and synthetic flood damage models: The case of Italy. *Natural Hazards and Earth System Sciences*, *19*(3), 661–678.

Apel, H., Aronica, G. T., Kreibich, H., & Thieken, A. H. (2009). Flood risk analyses: How detailed do we need to be? *Natural Hazards*, *49*, 79–98. https://doi.org/10.1007/s11069-008-9277-8

Apel, H., Merz, B., & Thieken, A. H. (2008). Quantification of uncertainties in flood risk assessments. *International Journal of River Basin Management*, *6*, 149–162. https://doi.org/10.1080/15715124.2008.9635344

Arrighi, C., Pregnolato, M., Dawson, R. J., & Castelli, F. (2019). Preparedness against mobility disruption by floods. *Science of the Total Environment*, *654*, 1010–1022. https://doi.org/10.1016/j.scitotenv.2018.11.191

Attems, M., Thaler, T., Genovese, E., & Fuchs, S. (2020). Implementation of property-level flood risk adaptation (PLFRA) measures: Choices and decisions. *WIREs Water*, *7*, 1–19. https://doi.org/10.1002/wat2.1404

Attems, M. S., Schlögl, M., Thaler, T., Rauter, M., & Fuchs, S. (2020). Risk communication and adaptive behaviour in flood-prone areas of Austria: A methodology study on opinions of affected homeowners. *PLoS One*, *15*, 1–21. https://doi.org/10.1371/journal.pone.0233551

Attems, M. S., Thaler, T., Snel, K. A., Davids, P., Hartmann, T., & Fuchs, S. (2020). The influence of tailored risk communication on individual adaptive behaviour. *International Journal of Disaster Risk Reduction*, *49*(101), 618. https://doi.org/10.1016/j.ijdrr.2020.101618

Barendrecht, M. H., Viglione, A., Kreibich, H., Merz, B., Vorogushyn, S., & Blöschl, G. (2019). The value of empirical data for estimating the parameters of a sociohydrological flood risk model. *Water Resources Research*, *55*, 1312–1336. https://doi.org/10.1029/2018WR024128

Barrington-Leigh, C., & Millard-Ball, A. (2017). The world's user-generated road map is more than 80 percent complete. *PLoS One*, *12*, 1–20. https://doi.org/10.1371/journal.pone.0180698

Bermúdez, M., & Zischg, A. P. (2018). Sensitivity of flood loss estimates to building representation and flow depth attribution methods in micro-scale flood modelling. *Natural Hazards*, *92*(3), 1633–1648. https://doi.org/10.1007/s11069-018-3270-7

Beven, K. (2001). *Rainfall-runoff modelling: The primer* (1st ed.). Wiley-Blackwell.

Bixler, R. P., Paul, S., Jones, J., Preisser, M., & Passalacqua, P. (2021). Unpacking adaptive capacity to flooding in urban environments: Social capital, social vulnerability, and risk perception. *Frontiers in Water*, *3*, 1–12. https://doi.org/10.3389/frwa.2021.728730

Blöschl, G., Hall, J., Parajka, J., Perdigão, R. A. P., Merz, B., Arheimer, B., Aronica, G. T., Bilibashi, A., Bonacci, O., Borga, M., Ivan, Č., Castellarin, A., Chirico, G. B., Claps, P., Fiala, K., Frolova, N., Gorbachova, L., Gül, A., Hannaford, J., … Živković, N. (2017). Changing climate shifts timing of European floods. *Science*, *357*, 588–590. https://doi.org/10.1126/science.aan2506

Blöschl, G., Kiss, A., Viglione, A., Barriendos, M., Böhm, O., Brázdil, R., Coeur, D., Demarée, G., Llasat, M. C., Macdonald, N., Retsö, D., Roald, L., Schmocker-Fackel, P., Amorim, I., Bělínová, M., Benito, G., Bertolin, C., Camuffo, D., Cornel, D., … Wetter, O. (2020). Current European flood-rich period exceptional compared with past 500 years. *Nature*, *583*, 560–566. https://doi.org/10.1038/s41586-020-2478-3

Blumenthal, B., & Nyberg, L. (2019). The impact of intense rainfall on insurance losses in two Swedish cities. *Journal of Flood Risk Management*, *12*(S2), e12504.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

Bronstert, A., Agarwal, A., Boessenkool, B., Crisologo, I., Fischer, M., Heistermann, M., Köhn-Reich, L., López-Tarazón, J., Moran, T., Ozturk, U., Reinhardt-Imjela, C., & Wendi, D. (2018). Forensic hydro-meteorological analysis of an extreme flash flood: The 2016-05-29 event in Braunsbach, SW Germany. *Science of the Total Environment*, *630*, 977–991.

Bronstert, A., Agarwal, A., Boessenkool, B., Fischer, M., Heistermann, M., Köhn-Reich, L., Moran, T., & Wendi, D. (2017). Die Sturzflut von Braunsbach am 29. Mai 2016 - Entstehung, Ablauf und Schäden eines "Jahrhundertereignisses." Teil 1: Meteorologische und Hydrologische Analysen. *Hydrologie und Wasserbewirtschaftung*, *61*(3), 150–162.

Bronstert, A., Crisologo, I., Heistermann, M., Ozturk, U., Vogel, K., & Wendi, D. (2020). Flash-floods: More often, more severe, more damaging? An analysis of hydro-geo-environmental conditions and anthropogenic impacts. In W. Leal, G. Nagy, M. Borga, D. Chavez, & A. Magnuszewski (Eds.), *Climate change, hazards and adaptation options. Handling the* *impacts of a changing climate* (pp. 225–244). Springer Nature. https://doi.org/10.1007/978-3-030-37425-9_12

Bronstert, A., Niehoff, D., & Bürger, G. (2002). Effects of climate and land-use change on storm runoff generation: Present knowledge and modelling capabilities. *Hydrological Processes*, *16*, 509–529. https://doi.org/10.1002/hyp.326

Brovelli, M. A., & Zamboni, G. (2018). A new method for the assessment of spatial accuracy and completeness of OpenStreetMap building footprints. *ISPRS International Journal of Geo-Information*, *7*, 1–25. https://doi.org/10.3390/ijgi7080289

Bubeck, P., Berghäuser, L., Hudson, P., & Thieken, A. H. (2020). Using panel data to understand the dynamics of human behaviour in response to flooding. *Risk Analysis*, *40*, 2340–2359. https://doi.org/10.1111/risa.13548

Bubeck, P., Botzen, W. J., Laudan, J., Aerts, J. C., & Thieken, A. H. (2018). Insights into flood-coping appraisals of protection motivation theory: Empirical evidence from Germany and France. *Risk Analysis*, *38*, 1239–1257. https://doi.org/10.1111/risa.12938

Bubeck, P., Dillenardt, L., Alfieri, L., Feyen, L., Thieken, A. H., & Kellermann, P. (2019). Global warming to increase flood risk on European railways. *Climatic Change*, *155*, 19–36. https://doi.org/10.1007/s10584-019-02434-5

Bürger, G., Heistermann, M., & Bronstert, A. (2014). Towards subdaily rainfall disaggregation via Clausius-Clapeyron. *Journal of Hydrometeorology*, *15*, 1303–1311.

Bürger, G., Pfister, A., & Bronstert, A. (2021). Zunehmende Starkregenintensitäten als Folge der Klimaerwärmung. Datenanalyse und Zukunftsprojektion - increasing intensity of heavy rainfall caused by global warming: Data analysis and future projections. *Hydrologie und Wasserbewirtschaftung*, *65*(6), 262–271. https://doi.org/10.5675/HyWa_2021.6_1

Carisi, F., Schröter, K., Domeneghetti, A., Kreibich, H., & Castellarin, A. (2018). Development and assessment of uni- and multivariable flood loss models for Emilia-Romagna (Italy). *Natural Hazards and Earth System Sciences*, *18*, 2057–2079. https://doi.org/10.5194/nhess-18-2057-2018

Chehreghan, A., & Ali Abbaspour, R. (2018). An evaluation of data completeness of VGI through geometric similarity assessment. *International Journal of Image and Data Fusion*, *9*, 319–337. https://doi.org/10.1080/19479832.2018.1504825

Chen, K., McAneney, J., Blong, R., Leigh, R., Hunter, L., & Magill, C. (2004). Defining area at risk and its effect in catastrophe loss estimation: a dasymetric mapping approach. *Applied Geography*, *24*, 97–117.

Cheng, L., & AghaKouchak, A. (2014). Nonstationary precipitation intensity-duration-frequency curves for infrastructure design in a changing climate. *Scientific Reports 4*, 7093, 1–6. https://doi.org/10.1038/srep07093

Chow, V. T. (1953). Frequency analysis of hydrologic data with special application to rainfall intensities. *University of Illinois Bulletin*, *50*, 86.

Chowdhary, H., & Singh, V. P. (2019). Multivariate frequency distributions in hydrology. In R. Teegavarapu, J. D. Salas, & J. Stedinger (Eds.), *Statistical distributions in hydrology*. ASCE Press.

Citeau, J. M. (2003). A new control concept in the oise catchment area: Definition and assessment of flood compatible agricultural activities. FIG Working Week, Paris, France.

Costabile, P., Costanzo, C., De Lorenzo, G., & Macchione, F. (2020). Is local flood hazard assessment in urban areas significantly influenced by the physical complexity of the hydrodynamic inundation model? *Journal of Hydrology*, *580*. https://doi.org/10.1016/j.jhydrol.2019.124231

Dazzi, S., Vacondio, R., & Mignosa, P. (2019). Integration of a levee breach erosion model in a GPU-accelerated 2D shallow water equations code. *Water Resources Research*, *55*, 682–702. https://doi.org/10.1029/2018WR023826

de Almeida, G. A., Bates, P., & Ozdemir, H. (2018). Modelling urban floods at submetre resolution: Challenges or opportunities for flood risk management? *Journal of Flood Risk Management*, *11*, S855–S865. https://doi.org/10.1111/jfr3.12276

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*, 865–890. https://doi.org/10.1007/s11027-015-9654-z

de Moel, H., van Alphen, J., & Aerts, J. C. (2009). Flood maps in Europe - Methods, availability and use. *Natural Hazards and Earth System Sciences*, *9*, 289–301. https://doi.org/10.5194/nhess-9-289-2009

de Ruig, L. T., Haer, T., de Moel, H., Botzen, W. J. W., & Aerts, J. C. J. H. (2020). A micro-scale cost-benefit analysis of building-level flood risk adaptation measures in Los Angeles. *Water Resources and Economics*, *32*, 100147. https://doi.org/10.1016/j.wre.2019.100147

Di Baldassarre, G., Kreibich, H., Vorogushyn, S., Aerts, J., Arnbjerg-Nielsen, K., Barendrecht, M., Bates, P., Borga, M., Botzen, W., Bubeck, P., de Marchi, B., Llasat, C., Mazzoleni, M., Molinari, D., Mondino, E., Mård, J., Petrucci, O., Scolobig, A., Viglione, A., & Ward, P. J. (2018). Hess opinions: An interdisciplinary research agenda to explore the unintended consequences of structural flood protection. *Hydrology and Earth System Sciences*, *22*(11), 5629–5637.

Di Baldassarre, G. D., Viglione, A., Carr, G., Kuil, L., Salinas, J. L., & Bl, G. (2013). Socio-hydrology: Conceptualising human-flood interactions. *Hydrology and Earth System Sciences*, *17*, 3295–3303. https://doi.org/10.5194/hess-17-3295-2013

Dietze, M., & Öztürk, U. (2021). A flood of disaster response challenges. *Science*, *373*(6561), 1317–1318.

Dittrich, R., Ball, T., Wreford, A., Moran, D., & Spray, C. J. (2019). A cost-benefit analysis of afforestation as a climate change adaptation measure to reduce flood risk. *Journal of Flood Risk Management*, *12*(4), 1–11. https://doi.org/10.1111/jfr3.12482

DKKV. (2022). Die Flutkatastrophe im Juli 2021 Deutschland (p. 51). Deutsches Komitee Katastrophenvorsorge e.V. (DKKV). https://www.dkkv.org/fileadmin/user_upload/DKKV_Schriftenreihe_Ausgabe_62.pdf

Dottori, F., Alfieri, L., Salamon, P., Bianchi, A., Feyen, L., & Lorini, V. (2016). Flood hazard map for Europe - 100-year return period. European Commission, Joint Research Centre (JRC) [Dataset]. http://data.europa.eu/89h/jrc-floods-floodmapeu_rp100y-tif

Dutta, D., Herath, S., & Musiake, K. (2003). A mathematical model for flood loss estimation. *Journal of Hydrology*, *277*, 24–49. https://doi.org/10.1016/S0022-1694(03)00084-2

Emanuelsson, M. A. E., Mcintyre, N., Hunt, C. F., Mawle, R., Kitson, J., & Voulvoulis, N. (2014). Flood risk assessment for infrastructure networks. *Journal of Flood Risk Management*, *7*, 31–41. https://doi.org/10.1111/jfr3.12028

European Commission (EC). (2007). *Directive 2007/60/EC of the European Parliament and of the Council of 23 October 2007 on the assessment and management of flood risks (floods directive)*. EC.

Fadel, A. W., Marques, G. F., Goldenfum, J. A., Medellín-Azuara, J., & Tilmant, A. (2018). Full flood cost: Insights from a risk analysis perspective. *Journal of Environmental Engineering*, *144*(9).

Falter, D., Schröter, K., Dung, N. V., Vorogushyn, S., Kreibich, H., Hundecha, Y., Apel, H., & Merz, B. (2015). Spatially coherent flood risk assessment based on long-term continuous simulation with a coupled model chain. *Journal of Hydrology*, *524*, 182–193. https://doi.org/10.1016/j.jhydrol.2015.02.021

Falter, D., Vorogushyn, S., Lhomme, J., Apel, H., Gouldby, B., & Merz, B. (2013). Hydraulic model evaluation for large-scale flood risk assessments. *Hydrological Processes*, *27*, 1331–1340. https://doi.org/10.1002/hyp.9553

Fan, H., Zipf, A., Fu, Q., & Neis, P. (2014). Quality assessment for building footprints data on OpenStreetMap. *International Journal of Geographical Information Science*, *28*, 700–719. https://doi.org/10.1080/13658816.2013.867495

Fauer, F. S., Ulrich, J., Jurado, O. E., & Rust, H. W. (2021). Flexible and consistent quantile estimation for intensity–duration–frequency curves. *Hydrology and Earth System Sciences*, *25*(12), 6479–6494.

Fewtrell, T. J., Duncan, A., Sampson, C. C., Neal, J. C., & Bates, P. D. (2011). Benchmarking urban flood models of varying complexity and scale using high resolution terrestrial LiDAR data. *Physics and Chemistry of the Earth*, *36*, 281–291. https://doi.org/10.1016/j.pce.2010.12.011

Floodlist. (2021). floodlist.com.

Förster, S., Lindenschmidt, K., Kuhlmann, B., & Bronstert, A. (2008). Assessing flood risk for a rural detention area. *Natural Hazards and Earth System Sciences*, *8*(2), 311–322.

Fuentes-Andino, D., Beven, K., Halldin, S., Xu, C. Y., Reynolds, J. E., & Di Baldassarre, G. (2017). Reproducing an extreme flood with uncertain post-event information. *Hydrology and Earth System Sciences*, *21*, 3597–3618. https://doi.org/10.5194/hess-21-3597-2017

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*, 1–22. 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. *Water Resources Bulletin*, *11*, 379–390. https://doi.org/10.1111/j.1752-1688.1975.tb00689.x

Grothmann, T., & Reusswig, F. (2006). People at risk of flooding: Why some residents take precautionary action while others do not. *Natural Hazards*, *38*, 101–120.

Gumbel, E. J. (1941). The return period of flood flows. *The Annals of Mathematical Statistics*, *12*, 163–190.

Haer, T., Botzen, W. J. W., de Moel, H., & Aerts, J. C. J. H. (2017). Integrating household risk mitigation behaviour in flood risk analysis: An agent-based model approach. *Risk Analysis*, *37*, 1977–1992. https://doi.org/10.1111/risa.12740

Haerter, J. O., Berg, P., & Hagemann, S. (2010). Heavy rain intensity distributions on varying time scales and at different temperatures. *Journal of Geophysical Research: Atmospheres*, *115*(17), 2156–2202.

Halbert, K., Nguyen, C. C., Payrastre, O., & Gaume, E. (2016). Reducing uncertainty in flood frequency analyses: A comparison of local and regional approaches involving information on extreme historical floods. *Journal of Hydrology*, *541*, 90–98. https://doi.org/10.1016/j.jhydrol.2016.01.017

Hardwick, J. R., Westra, S., & Sharma, A. (2010). Observed relationships between extreme sub-daily precipitation, surface temperature, and relative humidity. *Geophysical Research Letters*, *37*, 1–5. https://doi.org/10.1029/2010GL045081

Hasanzadeh Nafari, R., Ngo, T., & Mendis, P. (2016). An assessment of the effectiveness of tree-based models for multivariate flood damage assessment. *Water*, *8*(282), 1–18. https://doi.org/10.3390/w8070282

Hecht, R., Kunze, C., & Hahmann, S. (2013). Measuring completeness of building footprints in openstreetmap over space and time. *ISPRS International Journal of Geo-Information*, *2*, 1066–1091. https://doi.org/10.3390/ijgi2041066

Heidenreich, A., Masson, T., & Bamberg, S. (2020). Let's talk about flood risk – Evaluating a series of workshops on private flood protection. *International Journal of Disaster Risk Reduction*, *50*, 101880. https://doi.org/10.1016/j.ijdrr.2020.101880

Heistermann, M., Collis, S., Dixon, M. J., Giangrande, S., Helmus, J. J., Kelley, B., Koistinen, J., Michelson, D., Peura, M., Pfaff, T., & Wolff, D. B. (2015). The emergence of open source software for the weather radar community. *Bulletin of the American Meteorological Society*, *96*, 117–128. https://doi.org/10.1175/BAMS-D-13-00240.1

Heistermann, M., Jacobi, S., & Pfaff, T. (2013). Technical note: An open source library for processing weather radar data (wradlib). *Hydrology and Earth System Science*, *17*, 863–871.

Hosking, J., & Wallis, J. (1997). *Regional frequency analysis: An approach based on L-moments*. Cambridge University Press.

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*, *2*, 1731–1747. https://doi.org/10.5194/nhessd-2-681-2014

Hudson, P., Thieken, A. H., & Bubeck, P. (2020). The challenges of longitudinal surveys in the flood risk domain. *Journal of Risk Research*, *23*(5), 642–663. https://doi.org/10.1080/13669877.2019.1617339

Hunter, N. M., Bates, P. D., Neelz, S., Pender, G., Villanueva, I., Wright, N. G., Liang, D., Falconer, R. A., Lin, B., Waller, S., Crossley, A. J., & Mason, D. C. (2008). Benchmarking 2D hydraulic models for urban flooding. *Proceedings of the Institution of Civil Engineers: Water Management*, *161*, 13–30. https://doi.org/10.1680/wama.2008.161.1.13

IPCC. (2018). *Global warming of 1.5°C. An IPCC special report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change*. Cambridge University Press.

Jakeman, A. J., Letcher, R. A., & Norton, J. P. (2006). Ten iterative steps in development and evaluation of environmental models. *Environmental Modelling and Software*, *21*, 602–614. https://doi.org/10.1016/j.envsoft.2006.01.004

Keating, A., Campbell, K., Szoenyi, M., McQuistan, C., Nash, D., & Burer, M. (2017). Development and testing of a community flood resilience measurement tool. *Natural Hazards and Earth System Sciences*, *17*(1), 77–101.

Kellermann, P., Schönberger, C., & Thieken, A. H. (2016). Large-scale application of the flood damage model RAilway infrastructure loss (RAIL). *Natural Hazards and Earth System Sciences*, *16*, 2357–2371. https://doi.org/10.5194/nhess-16-2357-2016

Kemter, M., Merz, B., Marwan, N., Vorogushyn, S., & Blöschl, G. (2020). Joint trends in flood magnitudes and spatial extents across Europe. *Geophysical Research Letters*, *47*, 1–8. https://doi.org/10.1029/2020GL087464

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*, 505–526. https://doi.org/10.5194/nhess-15-505-2015

Kjeldsen, T. R., Macdonald, N., Lang, M., Mediero, L., Albuquerque, T., Bogdanowicz, E., Brazdil, R., Castellarin, A., David, V., Fleig, A., Gul, G. O., Kriauciuniene, J., Kohnova, S., Merz, B., Nicholson, O., Roald, L. A., Salinas, J. L., Sarauskiene, D., Sraj, M., … Wilson, D. (2014). Documentary evidence of past floods in Europe and their utility in flood frequency estimation. *Journal of Hydrology*, *517*, 963–973. https://doi.org/10.1016/j.jhydrol.2014.06.038

Kleist, L., Thieken, A. H., Köhler, P., Müller, M., Seifert, I., Borst, D., & Werner, U. (2006). Estimation of the regional stock of residential buildings as a basis for a comparative risk assessment in Germany. *Natural Hazards and Earth System Sciences*, *6*, 541–552. https://doi.org/10.5194/nhess-6-541-2006

Klijn, F., Kreibich, H., de Moel, H., & Penning-Rowsell, E. (2015). Adaptive flood risk management planning based on a comprehensive flood risk conceptualisation. *Mitigation and Adaptation Strategies for Global Change*, *20*, 845–864. https://doi.org/10.1007/s11027-015-9638-z

Koks, E. E., Rozenberg, J., Zorn, C., Tariverdi, M., Vousdoukas, M., Fraser, S. A., Hall, J. W., & Hallegatte, S. (2019). A global multi-hazard risk analysis of road and railway infrastructure assets. *Nature Communications*, *10*, 1–11. https://doi.org/10.1038/s41467-019-10442-3

Kousky, C., & Walls, M. (2014). Floodplain conservation as a flood mitigation strategy: Examining costs and benefits. *Ecological Economics*, *104*, 119–128. https://doi.org/10.1016/j.ecolecon.2014.05.001

Kreibich, H., Botto, A., Merz, B., & Schroeter, K. (2016). Probabilistic, multivariable flood loss modeling on the mesoscale with BT-FLEMO. *Society for Risk Analysis*, *37*, 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*, 967–989. https://doi.org/10.1007/s11027-014-9629-5

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*, 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: de 'Wrachien, D., Proverbs, D., Brebbia, C. A., Mambretti, S. (Eds.), *Flood Recovery, Innovation and Response II*, (Transactions on Ecology and the Environment; 133), WIT Press, 3–11.

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*, 1302–1314. https://doi.org/10.1080/02626667.2010.529815

Kreibich, H., Seifert, I., Thieken, A. H., Lindquist, E., Wagner, K., & Merz, B. (2011). Recent changes in flood preparedness of private households and businesses in Germany. *Regional Environmental Change*, *11*, 59–71. https://doi.org/10.1007/s10113-010-0119-3

Kreibich, H., & Thieken, A. H. (2008). Assessment of damage caused by high groundwater inundation. *Water Resources Research*, *44*, 1–14. https://doi.org/10.1029/2007WR006621

Kreibich, H., Thieken, A. H., Petrow, T., Müller, M., & Merz, B. (2005). Flood loss reduction of private households due to building precautionary measures – Lessons learned from the Elbe flood in August 2002. *Natural Hazards and Earth System Sciences*, *5*, 117–126. https://doi.org/10.5194/nhess-5-117-2005

Kreibich, H., Vorogushyn, S., Apel, H., Chinh, D., Gain, A., Dung, N., Schröter, K., Merz, B., Di Baldassarre, G., Mård, J., Aerts, J., Ward, P., Aronica, G., Arnbjerg-Nielsen, K., Bouwer, L., Slager, K., Bubeck, P., Thieken, A., Caloiero, T., … Molinari, D. (2017). Adaptation to flood risk: Results of international paired flood event studies. *Earth's Future*, *5*, 953–965. https://doi.org/10.1002/eft2.232

Kuhlicke, C., Masson, T., Kienzler, S., Sieg, T., Thieken, A. H., & Kreibich, H. (2020). Multiple flood experiences and social resilience: Findings from three surveys on households and companies exposed to the 2013 flood in Germany. *Weather, Climate, and Society*, *12*(1), 63–88. https://doi.org/10.1175/wcas-d-18-0069.1

Kuhlicke, C., Seebauer, S., Hudson, P., Begg, C., Bubeck, P., Dittmer, C., Grothmann, T., Heidenreich, A., Kreibich, H., Lorenz, D., Masson, T., Reiter, J., Thaler, T., Thieken, A. H., & Bamberg, S. (2020). The behavioural turn in flood risk management, its assumptions and potential implications. *WIREs Water*, *7*(3), e1418. https://doi.org/10.1002/wat2.1418

Kundzewicz, Z. W., Pin'skwar, I., & Brakenridge, G. R. (2018). Changes in river flood hazard in Europe: A review. *Hydrology Research*, *49*(2), 294–302. https://doi.org/10.2166/nh.2017.016

Kunz, M., Mühr, B., Kunz-Plapp, T., Daniell, J. E., Khazai, B., Wenzel, F., Vannieuwenhuyse, M., Comes, T., Elmer, F., Schröter, K., Fohringer, J., Münzberg, T., Lucas, C., & Zschau, J. (2013). Investigation of superstorm Sandy 2012 in a multi-disciplinary approach. *Natural Hazards and Earth System Sciences*, *13*, 2579–2598. https://doi.org/10.5194/nhess-13-2579-2013

Kvočka, D., Falconer, R. A., & Bray, M. (2015). Appropriate model use for predicting elevations and inundation extent for extreme flood events. *Natural Hazards*, *79*, 1791–1808. https://doi.org/10.1007/s11069-015-1926-0

Laudan, J., Rözer, V., Sieg, T., Vogel, K., & Thieken, A. H. (2017). Damage assessment in Braunsbach 2016: Data collection and analysis for an improved understanding of damaging processes during flash floods. *Natural Hazards and Earth System Sciences*, *17*, 2163–2179. https://doi.org/10.5194/nhess-17-2163-2017

Laudan, J., Zöller, G., & Thieken, A. H. (2020). Flash floods versus river floods-a comparison of psychological impacts and implications for precautionary behaviour. *Natural Hazards and Earth System Sciences*, *20*, 999–1023. https://doi.org/10.5194/nhess-20-999-2020

Lehmann, J., Mempel, F., & Coumou, D. (2018). Increased occurrence of record-wet and record-dry months reflect changes in mean rainfall. *Geophysical Research Letters*, *45*(24), 13468–13476.

Lenderink, G., & van Meijgaard, E. (2008). Increase in hourly precipitation extremes beyond expectations from temperature changes. *Nature Geoscience*, *1*(8), 511–514.

LUBW. (2015). *Abfluss-BW Regionalisierte Abfluss-Kennwerte Baden-Württemberg. Landesanstalt für Umwelt, Messungen und Naturschutz Baden-Württemberg. Referat 43*. Hydrologie, Hochwasservorhersage.

Lüdtke, S., Schröter, K., Steinhausen, M., Weise, L., Figueiredo, R., & Kreibich, H. (2019). A Consistent Approach for Probabilistic Residential Flood Loss Modeling in Europe. *Water Resources Research*, *55*(12), 10616–10635. Portico. https://doi.org/10.1029/2019wr026213

Menger, K. (1960). A counterpart of Occam's razor in pure and applied mathematics ontological uses. *Synthese*, *12*, 415–428. https://doi.org/10.1007/BF00485426

Merz, B., Elmer, F., & Thieken, A. H. (2009). Significance of "high probability/low damage" versus "low probability/high damage" flood events. *Natural Hazards and Earth System Sciences*, *9*, 1033–1046. https://doi.org/10.5194/nhess-9-1033-2009

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*, 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 Sciences*, *10*, 1697–1724. https://doi.org/10.5194/nhess-10-1697-2010

Merz, B., & Thieken, A. H. (2004). Flood risk analysis: Concepts and challenges. *Österreichische Wasser- und Abfallwirtschaft*, *56*, 27–34.

Merz, B., & Thieken, A. H. (2005). Separating natural and epistemic uncertainty in flood frequency analysis. *Journal of Hydrology*, *309*, 114–132. https://doi.org/10.1016/j.jhydrol.2004.11.015

Merz, B., & Thieken, A. H. (2009). Flood risk curves and uncertainty bounds. *Natural Hazards*, *51*(3), 437–458. https://doi.org/10.1007/s11069-009-9452-6

Merz, B., Vorogushyn, S., Lall, U., Viglione, A., & Blöschl, G. (2015). Charting unknown waters—On the role of surprise in flood risk assessment and management. *Water Resources Research*, *51*, 6399–6416. https://doi.org/10.1002/2015WR017464

Merz, R., & Blöschl, G. (2003). A process typology of regional floods. *Water Resources Research*, *39*, 1–20. https://doi.org/10.1029/2002WR001952

Metin, D., Nguyen, V. D., Schröter, K., Guse, B., Apel, H., Kreibich, H., Vorogushyn, S., & Merz, B. (2018). How do changes along the risk chain affect flood risk? *Natural Hazards and Earth System Sciences*, *18*, 3089–3108. https://doi.org/10.5194/nhess-18-3089-2018

Meyer, V., Haase, À. D., & Scheuer, S. (2009). Flood risk assessment in european river basins—Concept, methods, and challenges exemplified at the Mulde river. *Integrated Environmental Assessment and Management*, *5*, 17–26.

Mishra, V., Wallace, J. M., & Lettenmaier, D. P. (2012). Relationship between hourly extreme precipitation and local air temperature in the United States. *Geophysical Research Letters*, *39* (L16403), 1–7. https://doi.org/10.1029/2012GL052790

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*(6), e2019WR025943. https://doi.org/10.1029/2019WR025943

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

Molinari, D., Dazzi, S., Gattai, E., Minucci, G., Pesaro, G., Radice, A., & Vacondio, R. (2021). Cost–benefit analysis of flood mitigation measures: a case study employing high-performance hydraulic and damage modelling. *Natural Hazards*, *108*, 3061–3084. https://doi.org/10.1007/s11069-021-04814-6

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

Mueller, M., Fourty, T., & Assmann, A. (2013). BEAM and AM +: Two assets mapping products suited for multi-risk applications. In F. Klijn & T. Schweckendiek (Eds.), *Comprehensive flood risk management* (pp. 1045–1050). Taylor and Francis Group.

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.

Naulin, J. P., Moncoulon, D., & Quantin, A. (2019). Deterministic and probabilistic modeling of losses induced by coastal flooding in France. *Houille Blanche*, *105*(3-4), 130–139. https://doi.org/10.1051/lhb/2019022

Neal, J., Villanueva, I., Wright, N., Willis, T., Fewtrell, T., & Bates, P. (2012). How much physical complexity is needed to model flood inundation? *Hydrological Processes*, *26*, 2264–2282. https://doi.org/10.1002/hyp.8339

Neelz, S., & Pender, G. (2013). *Benchmarking the latest generation of 2D hydraulic modelling packages*. Environment Agency.

Niehoff, D., Fritsch, U., & Bronstert, A. (2002). Land-use impacts on storm-runoff generation: Scenarios of land-use change and simulation of hydrological response in a meso-scale catchment in SW-Germany. *Journal of Hydrology*, *267*, 80–93. https://doi.org/10.1016/S00221694(02)00142-7

Otto, A., Kellermann, P., Thieken, A. H., Manez Costa, M., Carmona, M., & Bubeck, P. (2019). Risk reduction partnerships for assessing and enhancing resilience of railway transport infrastructure in an alpine environment. *International Journal of Disaster Risk Reduction*, *33*, 385–397. https://doi.org/10.1016/j.ijdrr.2018.10.025.ich

Ozturk, U., Wendi, D., Crisologo, I., Riemer, A., Agarwal, A., Vogel, K., López-Tarazón, J. A., & Korup, O. (2018). Rare flash floods and debris flows in southern Germany. *Science of the*

Total Environment, *626*, 941–952. https://doi.org/10.1016/j.scitotenv.2018.01.172

Panthou, G., Mailhot, A., Laurence, E., & Talbot, G. (2014). Relationship between surface temperature and extreme rainfalls: A multi-time-scale and event-based analysis. *Journal of Hydrometeorology*, *15*(5), 1999–2011.

Papaioannou, G., Loukas, A., Vasiliades, L., & Aronica, G. T. (2016). Flood inundation mapping sensitivity to riverine spatial resolution and modelling approach. *Natural Hazards*, *83*, 117–132. https://doi.org/10.1007/s11069-016-2382-1

Paprotny, D., Kreibich, H., Morales-Nápoles, O., Terefenko, P., & Schröter, K. (2020). Estimating exposure of residential assets to natural hazards in Europe using open data. *Natural Hazards and Earth System Sciences*, *20*, 323–343. https://doi.org/10.5194/nhess-20-323-2020

Penning-Rowsell, E. C., Priest, S., Parker, D. J., Morris, J., Tunstall, S., Viavattene, C., Chatterton, J., & Owen, D. (2013). *Flood and coastal erosion risk management: a manual for economic appraisal*. Routledge.

Persi, E., Petaccia, G., & Sibilla, S. (2018). Large wood transport modelling by a coupled Eulerian–Lagrangian approach. *Natural Hazards*, *91*, 59–74. https://doi.org/10.1007/s11069-017-2891-6

Pescaroli, G., & Alexander, D. (2018). Understanding compound, interconnected, interacting, and cascading risks: A holistic framework. *Risk Analysis*, *38*(11), 2245–2257. https://doi.org/10.1111/risa.13128

Pittore, M., Wieland, M., & Fleming, K. (2017). Perspectives on global dynamic exposure modelling for geo-risk assessment. *Natural Hazards*, *86*, 7–30. https://doi.org/10.1007/s11069-016-2437-3

Poussin, J. K., Botzen, W. J. W., & 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

Prahl, B. F., Rybski, D., Boettle, M., & Kropp, J. P. (2016). Damage functions for climate-related hazards: Unification and uncertainty analysis. *Natural Hazards and Earth System Sciences*, *16*, 1189–1203. https://doi.org/10.5194/nhess-16-1189-2016

Rogers, R. W. (1983). Cognitive and physiological processes in fear appeals and attitude change: A revised theory of protection motivation. In J. Cacioppo & R. Petty (Eds.), *Social psychophysiology*. Guilford Press.

Rogger, M., Agnoletti, M., Alaoui, A., Bathurst, J. C., Bodner, G., Borga, M., Chaplot, V., Gallart, F., Glatzel, G., Hall, J., Holden, J., Holko, L., Horn, R., Kiss, A., Quinton, J. N., Leitinger, G., Lennartz, B., Parajka, J., Peth, S., … Viglione, A. (2017). Land use change impacts on floods at the catchment scale: Challenges and opportunities for future research. *Water Resources Research*, *53*, 5209–5219. https://doi.org/10.1002/2017WR020723.Received

Rogger, M., Kohl, B., Pirkl, H., Viglione, A., Komma, J., Kirnbauer, R., Merz, R., & Blöschl, G. (2012). Runoff models and flood frequency statistics for design flood estimation in Austria: Do they tell a consistent story? *Journal of Hydrology*, *456-457*, 30–43. https://doi.org/10.1016/j.jhydrol.2012.05.068

Röthlisberger, V., Zischg, A. P., & Keiler, M. (2018). A comparison of building value models for flood risk analysis. *Natural Hazards and Earth System Sciences*, *18*, 2431–2453. https://doi.org/10.5194/nhess-18-2431-2018

Rottler, E., Francke, T., Bürger, G., & Bronstert, A. (2020). Long-term changes in central European river discharge 1869–2016: Impact of changing snow covers, reservoir constructions and an intensified hydrological cycle. *Hydrology and Earth System Sciences*, *24*, 1721–1740. https://doi.org/10.5194/hess-24-1721-2020

Rottler, E., Kormann, C., Francke, T., & Bronstert, A. (2019). Elevation-dependent warming in the Swiss Alps 1981–2017: Features, forcings and feedbacks. *International Journal of Climatology*, *39*, 2556–2568. https://doi.org/10.1002/joc.5970

Rözer, V., Kreibich, H., Schröter, K., Müller, M., Sairam, N., Doss-Gollin, J., Lall, U., & Merz, B. (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., Pech, I., Schröter, K., Buchholz, O., & Kreibich, H. (2016). Coping with pluvial floods by private households. *Water*, *8*(7), 304. https://doi.org/10.3390/w8070304

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

Saltikoff, E., Friedrich, K., Soderholm, J., Lengfeld, K., Nelson, B., Becker, A., Hollmann, R., Urban, B., Heistermann, M., & Tassone, C. (2019). An overview of using weather radar for climatological studies successes, challenges, and potential. *Bulletin of the American Meteorological Society*, *100*, 1739–1751. https://doi.org/10.1175/BAMS-D-18-0166.1

Sanders, B. F., & Schubert, J. E. (2019). PRIMo: Parallel raster inundation model. *Advances in Water Resources*, *126*, 79–95. https://doi.org/10.1016/j.advwatres.2019.02.007

Sarhadi, A., & Soulis, E. D. (2017). Time-varying extreme rainfall intensity-duration-frequency curves in a changing climate. *Geophysical Research Letters*, *44*, 2454–2463. https://doi.org/10.1002/2016GL072201

Savant, G., Trahan, C. J., Pettey, L., McAlpin, T. O., Bell, G. L., & Mcknight, C. J. (2019). Urban and overland flow modeling with dynamic adaptive mesh and implicit diffusive wave equation solver. *Journal of Hydrology*, *573*, 13–30. https://doi.org/10.1016/j.jhydrol.2019.03.061

Schoppa, L., Sieg, T., Vogel, K., Zöller, G., & Kreibich, H. (2020). Probabilistic flood loss models for companies. *Water Resources Research*, *56*, 1–19. https://doi.org/10.1029/2020WR027649

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

Serago, J. M., & Vogel, R. A. (2018). Parsimonious nonstationary flood frequency analysis. *Advances in Water Resources*, *112*, 1–16. https://doi.org/10.1016/j.advwatres.2017.11.026

Sieg, T., Schinko, T., Vogel, K., Mechler, R., Merz, B., & Kreibich, H. (2019). Integrated assessment of short-term direct and indirect economic flood impacts including uncertainty quantification. *PLoS One*, *14*, 1–21. https://doi.org/10.1371/journal.pone.0212932

Sieg, T., & Thieken, A. H. (2022). Improving flood impact estimations. *Environmental Research Letters*, *17*(6), 064007. https://doi.org/10.1088/1748-9326/ac6d6c

Sieg, T., Vogel, K., Merz, B., & Kreibich, H. (2017). Tree-based flood damage modeling of companies: Damage processes and model performance. *Water Resources Research*, *53*, 1–19. https://doi.org/10.1002/2017WR020784

Sieg, T., Vogel, K., Merz, B., & Kreibich, H. (2019). Seamless estimation of hydrometeorological risk across spatial scales. *Earth's Future*, *7*, 574–581. https://doi.org/10.1029/2018EF001122

Simpson, N. P., Mach, K. J., Constable, A., Hess, J., Hogarth, R., Howden, M., Lawrence, J., Lempert, R. J., Muccione, V., Mackey, B., New, M. G., O'Neill, B., Otto, F., Pörtner, H.-O., Reisinger, A., Roberts, D., Schmidt, D. N., Seneviratne, S., Strongin, S., … Trisos, C. H. (2021). A framework for complex climate change risk assessment. *One Earth*, *4*, 489–501. https://doi.org/10.1016/j.oneear.2021.03.005

Smith, J. A., Cox, A. A., Baeck, M. L., Yang, L., & Bates, P. (2018). Strange floods: The upper tail of flood peaks in the United States. *Water Resources Research*, *54*(9), 6510–6542. https://doi.org/10.1029/2018WR022539

Spekkers, M. H., Kok, M., Clemens, F. H. L. R., & Ten Veldhuis, J. A. E. (2014). Decision-tree analysis of factors influencing rainfall-related building structure and content damage. *Natural Hazards and Earth System Sciences*, *14*(9), 2531–2547.

Stedinger, J. R. (2017). Flood frequency analysis. In V. P. Singh (Ed.), *Handbook of applied hydrology*. McGraw-Hill Education.

Sultana, Z., Sieg, T., Kellermann, P., Müller, M., & Kreibich, H. (2018). Assessment of business interruption of flood-affected companies using random forests. *Water*, *10*, 1–16. https://doi.org/10.3390/w10081049

Suppasri, A., Pakoksung, K., Charvet, I., Ting Chua, C., Takahashi, N., Ornthammarath, T., Latcharote, P., Leelawat, N., & Imamura, F. (2019). Load-resistance analysis: An alternative approach to tsunami damage assessment applied to the 2011 Great East Japan tsunami. *Natural Hazards and Earth System Sciences*, *19*, 1807–1822. https://doi.org/10.5194/nhess-19-1807-2019

Tate, E., Muñoz, C., & Suchan, J. (2015). Uncertainty and Sensitivity Analysis of the HAZUS-MH Flood Model. *Natural Hazards Review*, *16*(3). https://doi.org/10.1061/(asce)nh.1527-6996.0000167

Thieken, A., Kreibich, H., Müller, M., & Lamond, J. (2017). Data collection for a better understanding of what causes flood damage – Experiences with telephone surveys. In D. Molinari, S. Menoni, & F. Ballio (Eds.), *Flood damage survey and assessment: New insights from research and practice* (pp. 95–106). AGU, Wiley. https://doi.org/10.1002/9781119217930.ch7

Thieken, A. H., Cammerer, H., Dobler, C., Lammel, J., & Schöberl, F. (2016). Estimating changes in flood risks and benefits of non-structural adaptation strategies: A case study from Tyrol, Austria. *Mitigation and Adaptation Strategies for Global Change*, *21*, 343–376. https://doi.org/10.1007/s11027-014-9602-3

Thieken, A. H., Kienzler, S., Kreibich, H., Kuhlicke, C., Kunz, M., Mühr, B., Müller, M., Otto, A., Petrow, T., Pisi, S., & Schröter, K. (2016). Review of the flood risk management system in Germany after the major flood in 2013. *Ecology and Society*, *21*(2), 51. https://doi.org/10.5751/ES-08547-210251

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.

Thieken, A. H., Müller, M., Kleist, L., Seifert, I., Borst, D., & Werner, U. (2006). Regionalisation of asset values for risk analyses. *Natural Hazards and Earth System Sciences*, *6*, 167–178. https://doi.org/10.5194/nhess-6-167-2006

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. *WIT Transactions on Ecology and the Environment*, *118*, 315–324. https://doi.org/10.2495/FRIAR080301

Thomas Steven Savage, J., Pianosi, F., Bates, P., Freer, J., & Wagener, T. (2016). Quantifying the importance of spatial resolution and other factors through global sensitivity analysis of a flood inundation model. *Water Resources Research*, *52*(11), 9146–9163. Portico. https://doi.org/10.1002/2015wr018198

Ulrich, J., Fauer, F. S., & Rust, H. W. (2021). Modeling seasonal variations of extreme rainfall on different timescales in Germany. *Hydrology and Earth System Sciences*, *25*(12), 6133–6149.

Ulrich, J., Jurado, O. E., Peter, M., Scheibel, M., & Rust, H. W. (2020). Estimating IDF curves consistently over durations with spatial covariates. *Water*, *12*, 3119.

UNDRR. (2021). 2021 Annual Report. UN Office for Disaster Risk Reduction.

UNDRR & CRED. (2020). *Human cost of disasters - an overview of the last 20 years 2000–2019*. UN Office for Disaster Risk Reduction.

Urban Atlas. (2021). https://land.copernicus.eu/local/urban-atlas

van Ootegem, L., van Herck, K., Creten, T., Verhofstadt, E., Foresti, L., Goudenhoofdt, E., Reyniers, M., Delobbe, L., Murla Tuyls, D., & Willems, P. (2018). Exploring the potential of multivariate depth-damage and rainfall-damage models. *Journal of Flood Risk Management*, *11*, S916–S929.

van Ootegem, L., Verhofstadt, E., van Herck, K., & Creten, T. (2015). Multivariate pluvial flood damage models. *Environmental Impact Assessment Review*, *54*, 91–100.

van Valkengoed, A. M., & Steg, L. (2019). Meta-analyses of factors motivating climate change adaptation behaviour. *Nature Climate Change*, *9*, 158–163. https://doi.org/10.1038/s41558-018-0371-y

Viglione, A., Merz, R., Salinas, J. L., & Blöschl, G. (2013). Flood frequency hydrology: 3. A Bayesian analysis. *Water Resources Research*, *49*, 675–692. https://doi.org/10.1029/2011WR010782

Vogel, K., Ozturk, U., Riemer, A., Laudan, J., Sieg, T., Wendi, D., Agarwal, A., Rözer, V., Korup, O., & Thieken, A. (2017). Die Sturzflut von Braunsbach am 29. Mai 2016 – Entstehung, Ablauf und Schäden eines "Jahrhundertereignisses". *Teil 2: Geomorphologische Prozesse und Schadensanalyse - Hydrologie & Wasserbewirtschaftung*, *61*(3), 163–175. https://doi.org/10.5675/HyWa_2017.3_2

Vogel, K., Riggelsen, C., Merz, B., Kreibich, H., & Scherbaum, F. (2012). Flood damage and influencing factors: A Bayesian network perspective. In 6th European workshop on probabilistic graphical models (PGM 2012), University of Granada, Granada, Spain.

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

Vormoor, K., Lawrence, D., Heistermann, M., & Bronstert, A. (2015). Climate change impacts on the seasonality and generation processes of floods: Projections and uncertainties for catchments with mixed snowmelt/ rainfall regimes. *Hydrology and Earth System Sciences*, *19*, 913–931.

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

Ward, P. J., Jongman, B., Weiland, F. S., Bouwman, A., Beek, R. V., Bierkens, M. F. P., Ligtvoet, W., & Winsemius, H. (2013). Assessing flood risk at the global scale: Model setup, results, and sensitivity. *Environmental Research Letters*, *8*, 1–10. https://doi.org/10.1088/1748-9326/8/4/044019

Wieland, M., & Pittore, M. (2017). A Spatio-temporal building exposure database and information life-cycle management solution. *ISPRS International Journal of Geo-Information*, *6*, 114. https://doi.org/10.3390/ijgi6040114

Willner, S. N., Otto, C., & Levermann, A. (2018). Global economic response to river floods. *Nature Climate Change*, *8*, 1–5. https://doi.org/10.1038/s41558-018-0173-2

Wing, O. E. J., Quinn, N., Bates, P. D., Neal, J. C., Smith, A. M., Sampson, C. C., Coxon, G., Yamazaki, D., Sutanudjaja, E. H., & Alfieri, L. (2020). Toward global stochastic river flood modeling. *Water Resources Research*, *56*(8), e2020WR027692.

Winter, B., Schneeberger, K., Dung, N. V., Huttenlau, M., Achleitner, S., Stötter, J., Merz, B., & Vorogushyn, S. (2019). A continuous modelling approach for design flood estimation on sub-daily time scale. *Hydrological Sciences Journal*, *64*, 539–554. https://doi.org/10.1080/02626667.2019.1593419

Woodward, M., Kapelan, Z., & Gouldby, B. (2014). Adaptive flood risk management under climate change uncertainty using real options and optimization. *Risk Analysis*, *34*, 75–92. https://doi.org/10.1111/risa.12088

Wu, J., Ye, M., Wang, X., & Koks, E. (2019). Building asset value mapping in support of flood risk assessments: A case study of Shanghai, China. *Sustainability (Switzerland)*, *11*, 1–19. https://doi.org/10.3390/su11040971

Wünsch, A., Herrmann, U., Kreibich, H., & Thieken, A. H. (2009). The role of disaggregation of asset values in flood loss estimation: A comparison of different modeling approaches at the mulde river, Germany. *Environmental Management*, *44*, 524–541. https://doi.org/10.1007/s00267-009-9335-3

Xing, Y., Shao, D., Ma, X., Zhang, S., & Jiang, G. (2021). Investigation of the importance of different factors of flood inundation modeling applied in urbanized area with variance-based global sensitivity analysis. *Science of The Total Environment*, *772*, 145327. https://doi.org/10.1016/j.scitotenv.2021.145327

Yamazaki, D., de Almeida, G. A. M., & Bates, P. D. (2013). Improving computational efficiency in global river models by implementing the local inertial flow equation and a vector-based river network map. *Water Resources Research*, *49*, 7221–7235. https://doi.org/10.1002/wrcr.20552

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