https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Review article: Exploring methods capturing vulnerability dynamics in the context of flood hazard research

Julius Schlumberger[1,2,*], Tristian R. Stolte[2,*], Helena M. Garcia[3], Antonia Sebastian[3,4], Wiebke Jäger[2], Philip J. Ward[1,2], Marleen C. de Ruiter[2], Robert Šakić Trogrlić[5], Annegien Tijssen[1], and Mariana Madruga de Brito[6]

[1]Climate Adaptation and Disaster Risk Department, Deltares, The Netherlands
[2]Institute for Environmental Studies, Department of Water & Climate Risk, Vrije Universiteit Amsterdam, The Netherlands
[3]Environment, Ecology and Energy Program, University of North Carolina at Chapel Hill, USA
[4]Department of Earth, Marine and Environmental Sciences, University of North Carolina at Chapel Hill, NC USA
[5]International Institute for Applied Systems Analysis (IIASA), 2361 Laxenburg, Austria
[6]Department of Urban and Environmental Sociology, UFZ-Helmholtz Centre for Environmental Research, Leipzig, Germany
[*]These authors contributed equally to this work.

Correspondence: Mariana Madruga de Brito (mariana.brito@ufz.de)

Abstract. Flood vulnerability is highly dynamic, shaped by evolving social, economic, physical, and environmental conditions. Yet, most flood risk assessments still treat vulnerability as static, overlooking how these characteristics evolve and interact with one another. Here, we investigate how dynamic vulnerability in the context of flood risk is considered in 67 studies that use (a) indicator-based, (b) curve-based, (c) dynamic simulation models, (d) qualitative analysis, or (e) statistical analysis of sub-dimensions of vulnerability. Specifically, we examine the conceptual focus (ex-post, during the event, ex-ante), the type of dynamics (event-related, underlying, or complexity-caused), the dimensions of vulnerability captured, and the sources of data used. We find that curve-based approaches were used to address all types of dynamics and conceptual foci, but often in connection with quantitative impact modelling. Dynamic simulation models offered the richest representations of dynamics due to behavioural and systemic complexity but required significant data and computational resources, and faced challenges of model calibration and validation. Indicator-based approaches were effective in capturing underlying socio-economic and environmental changes, though often at coarse temporal resolution. Qualitative methods provided deep insights into the processes and contexts shaping vulnerability. Statistical analyses overlapped conceptually with indicator approaches but tended to focus more narrowly on event-related processes and specific sub-dimensions of vulnerability. Based on our review, we identify three priorities for advancing dynamic flood vulnerability research: leveraging scenarios to explore future change, improving causal inference, and improving data availability and resolution. Additionally, we encourage the flood risk research community to look to other hazard communities or research disciplines that work on systemic or dynamic processes, which might offer inspiration or novel approaches to assessing flood vulnerability dynamics.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

1 Introduction

Vulnerability is a central component of understanding disaster risk, shaping how severely individuals, communities, and other elements at risk are affected by natural hazards. It reflects a combination of social, economic, and physical characteristics that make an exposed element susceptible to harm (UNDRR, 2017; IPCC, 2022). As the severity and damages of floods are increasing (Rentschler et al., 2022; Tellman et al., 2021; van Loenhout and McClean, 2020), vulnerability plays a critical role in guiding effective flood risk reduction and management (Hinkel et al., 2021). Importantly, vulnerability helps to explain the uneven impacts of disasters and why similar flood events lead to different outcomes due to underlying conditions (e.g., poverty, infrastructure deficiencies, or mismanagement) (Choong et al., 2025). As such, understanding vulnerability enables decision-makers to move beyond hazard control or exposure reduction alone, toward more comprehensive risk reduction strategies that address the root causes of vulnerability.

Vulnerability is a dynamic concept (Cardona et al., 2012), varying both in space and time. It can shift in response to demographic changes, socio-economic developments, or experiences with and recovery from past impacts (Alwang et al., 2001; Sauer et al., 2024). For example, vulnerability may increase during economic crises, reducing an individual's or community's capacity to invest in adaptation measures (Matanó et al., 2022). At the same time, uninsured losses and property devaluation after a flood can increase the likelihood of abandonment and the financial instability for affected homeowners (Thomson et al., 2023). Additionally, a farmer dealing with flood damage might be limited in their recovery efforts in case of simultaneous or preceding hazards, e.g., by limitations to find field workers during pandemic lockdowns (Begum et al., 2023). These examples underscore that vulnerability is not only shaped by underlying conditions but also by cascading and compounding effects within society, particularly in multi-hazard contexts (de Ruiter and van Loon, 2022). Vulnerability should thus be addressed as a dynamic, multidimensional, and context-dependent concept (Cutter, 1996; de Ruiter et al., 2020).

A wide range of qualitative, quantitative, and mixed-method approaches have been developed to assess natural hazards vulnerability (for an overview, see e.g., Douglas, 2007; Hagenlocher et al., 2019; Nasiri et al., 2016; Simmons et al., 2017). Broadly, Fuchs et al. (2012) distinguish between deductive and inductive approaches. Deductive approaches typically apply theory-driven frameworks, such as indicator-based indices or fragility curves. Conversely, inductive approaches derive understanding from observed data or stakeholder input, as seen in participatory methods or data-driven statistical analyses. These methodological choices reflect diverse disciplinary perspectives and serve various purposes (Moret, 2014): some are used to directly inform or evaluate policies or local actions, while others aim instead to feed into risk assessment approaches. Joakim et al. (2016) further differentiates between conceptual approaches to vulnerability, ranging from vulnerability as a factor (i.e., used to determine impacts and adaptation needs), as a pre-existing condition (i.e., used to describe the state of an element at risk), or as an outcome (i.e., emerging as a consequence of impacts, DRM, and adaptation). Finally, some vulnerability assessments target the physical susceptibility of infrastructure or buildings to floods (e.g., Merz et al., 2010), while others emphasize social and economic factors affecting human well-being (e.g., Tate, 2012).

Despite this methodological diversity, several reviews have noted that existing approaches often treat vulnerability as a static state (Moreira et al., 2021), providing limited insight into how it evolves over time or in response to events and interventions.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

The dynamic nature of vulnerability has prompted calls for studies that account for its spatio-temporal evolution (e.g., Handmer et al., 1999; Birkmann et al., 2013; Buijs et al., 2025; Fuchs et al., 2013; Simpson et al., 2021; Ward et al., 2022). For instance, a systematic review of 95 flood vulnerability indices by Moreira et al. (2021) concluded that limited consideration is given to the dynamic characteristics of vulnerability, with most assessments applying a pre-event vulnerability lens and giving limited attention to assessments after floods (e.g. Carlier et al., 2018; Miguez and Veról, 2017). Similarly, a review by Jurgilevich et al. (2017) showed that sub-national climate risk assessments rarely address changes in risk and vulnerability over time. Other reviews have explored related aspects, including the sub-dimensions of social vulnerability considered in multi-hazard contexts Drakes and Tate (2022) and the extent to which global flood risk assessments account for vulnerability dynamics Ward et al. (2020a). While these reviews raise the lack of consideration of dynamic aspects in vulnerability assessment, none have analyzed the methodological approaches used to assess it. However, conceptual advances in the field do exist. For example, Mazzorana et al. (2012) offer a conceptual mathematical framework to allow for dynamic flood risk assessments, accounting for the changes in vulnerability due to previous damages and risk mitigation efforts as part of the recovery. Schröter et al. (2014), compares the performance of different damage models, including curve-based and data-mining approaches, when transferred to a different context or different flood event. Likewise, de Ruiter and van Loon (2022) propose a typology of vulnerability dynamics and suggest relevant methodological directions. These examples demonstrate the need for a targeted review of recent advances in current assessment methods and how they capture vulnerability dynamics within flood hazard research.

This review addresses this gap by analyzing methodological applications to showcase how flood vulnerability assessment methods have been used or adapted to capture vulnerability dynamics. Specifically, we examine: (1) the nature of change in vulnerability; (2) which sub-dimensions of vulnerability are considered; (3) the types of data and methods used; and (4) reported limitations. By exploring methodological applications across these analytical aspects, we offer practical recommendations for researchers seeking to incorporate dynamic vulnerability in their own studies. We also offer insights that can inform future applications or refinements of assessment methods for dynamic vulnerability, and inspire investigation into different fields, such as various hazard disciplines or thematic focus areas, including health, finance, and other sub-dimensions of vulnerability. It should be noted that this review does not aim to be systematic; rather, it provides a structured synthesis of current methodological practices and emerging directions in assessing dynamic vulnerability.

2 Theoretical perspectives on vulnerability

Vulnerability is a concept with multiple interpretations and no single, universally accepted definition. It is also difficult to comprehensively measure vulnerability, mostly because of its latent intangible and multidimensional character (Spielman et al., 2020; Giupponi et al., 2013). This conceptual ambiguity is further compounded, or perhaps even caused, by overlaps with related concepts such as resilience, sensitivity, and susceptibility (e.g., Birkmann et al., 2013; Gallopín, 2006; Miller et al., 2010) and by its different theoretical underpinnings, such as socio-ecological system thinking or disaster and climate risk reduction (Eakin and Luers, 2006; Fekete et al., 2014; Turner et al., 2003; Wisner et al., 2004). To provide conceptual clarity, the United Nations Office for Disaster Risk Reduction (UNDRR) and the Intergovernmental Panel on Climate Change (IPCC)

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

offer widely recognized definitions that help anchor vulnerability within disaster and climate risk frameworks. UNDRR (2017) defines vulnerability as "the conditions determined by physical, social, economic, and environmental factors or processes that increase the susceptibility of an individual, community, assets, or systems to the impacts of hazards". Similarly, IPCC (2022) frames vulnerability as "the propensity or predisposition to be adversely affected". Both definitions understand vulnerability as the combination of characteristics that determine the possibility of adverse impacts.

In this review, we adopt a flexible interpretation of the IPCC and UNDRR definitions. We recognize vulnerability as determined by various factors that shape the propensity of elements at risk to suffer harm. We thus include studies that touch upon factors influencing the magnitude of impacts conditional on exposure to flooding, enabling us to include studies where vulnerability is framed as 'coping capacity' or 'sensitivity' when considering the potential for adverse impacts. However, we also explicitly distinguish our use of vulnerability from applications that conflate vulnerability with exposure, commonly defined as the presence of people, infrastructure and other assets in hazard-prone areas (UNDRR, 2017) or hazard susceptibility, commonly understood as the underlying conditions of a place that make it prone to experiencing the effects of a specific hazard. Such conflation is common, for example, in coastal vulnerability assessments, where indicators such as elevation or proximity to the coastline are included under the umbrella of "vulnerability" (e.g., Ahmed et al., 2022; Barik et al., 2021; Bera and Maiti, 2021; Domeneghetti et al., 2015), or coastal erosion/sea level rise is framed as a change of vulnerability (e.g., Hastuti et al., 2022; Hoque et al., 2019; Islam et al., 2023; Kantamaneni et al., 2018). These approaches tend to embed hazard-specific or geographical factors into their definitions, thereby collapsing the conceptual distinction between vulnerability, exposure, and hazard. Similarly, studies that claimed to investigate vulnerability/risk changes primarily driven by population growth (e.g., Ballesteros and Esteves, 2021; Herslund et al., 2016; Ku et al., 2021; Londe et al., 2015) were also not considered. While such approaches can be helpful in localized risk assessments, they diverge from our more generalizable and systemic framing. In this study, we therefore do not adopt such interpretations of vulnerability.

3 Methods

This literature review follows a semi-systematic approach (Wong et al., 2013). A fully systematic review was not feasible because the potential body of relevant literature is extremely large and diffuse; for example, a simple Scopus query using `TITLE-ABS-KEY (vulnerability AND dynamic*)` returned over 30,000 hits in July 2025. While the concept of dynamic vulnerability has been recognized in theory for decades (Cutter, 1996), its empirical operationalization remains limited and the terminology inconsistent. In fact, the studies that do analyze vulnerability dynamics often do not describe them as dynamic but rather define them as vulnerability "shifts" or "changes". Given the emerging and interdisciplinary nature of this field, our aim was not to produce an exhaustive inventory of existing studies or measure effect sizes, but rather to identify key research traditions, synthesise methodological approaches, and detect recurring patterns and challenges. To achieve this, we adopted a qualitative, directed content analysis (Hsieh and Shannon, 2005) structured around a predefined set of categories (Table 1). This meta-narrative strategy based on semi- or non-systematic reviews (Snyder, 2019) has been applied in other

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

influential reviews on disaster risk management and climate change adaptation (e.g., de Angeli et al., 2022; Barendrecht et al., 2024; Ford et al., 2025; Petzold et al., 2020; Ward et al., 2020a, b).

The review process followed two main steps. First, an initial scoping phase combined exploratory Google Scholar searches with inputs from co-authors (see Appendix A for details). In this first step, we identified and analyzed 28 relevant articles. This stage allowed us to refine search terms for the semi-systematic review. It also allowed us to develop and refine the classification categories for the content analysis. In the second step, we conducted targeted searches in the Scopus database (July 2025) using queries that combined methodological terms (e.g., curve-based, simulation, indicator-based, qualitative, or statistical approaches) with flood-related keywords (e.g., flood, flood risk), vulnerability-related concepts (e.g., vulnerability, resilience, adaptive capacity), and temporal or dynamic aspects (e.g., longitudinal, recovery, adaptation). The queries are listed in Appendix B. Each query returned approximately 100 studies, totaling 620 articles. These studies were then screened for relevance by co-authors with expertise in the respective methods. We included only peer-reviewed, English-language studies and excluded those that did not address vulnerability dynamics. When eligibility was unclear, a second reviewer assessed the study, and inclusion decisions were made collectively. The final set of 67 relevant publications, including the 28 studies identified in the scoping phase, was reviewed in detail by at least one co-author, following the categories shown in Table 1. Some categories followed existing typologies (e.g., physical and social vulnerability sub-dimensions summarized in Table 2), while others were adapted from the literature. Reviewers were asked to provide a free-text elaboration for some of the categories, regarding the key findings of the study, and the limitations mentioned. The definitions for each of the adapted categories are described in the next sections.

Table 1. Categories used to characterize the analysed publications. These categories were defined based on the scoping review of 28 articles

Categories	**Options**	
Methodological approach	(a) Indicator-based; (b) Curve-based; (c) Dynamic simulation models; (d) Qualitative analysis; (e) Statistical analysis of sub-dimensions of vulnerability	Section 3.1
Conceptual focus	Vulnerability as a (a) Precondition; (b) Factor; (c) Outcome	Section 3.2
Type of dynamics	(a) Event-related dynamics, (b) Underlying dynamics, (c) Complexity dynamics	Section 3.3
Social vulnerability sub-dimensions	(a) Awareness & Information; (b) Crime & Conflict; (c) Culture & Behavior; (d) Demographic; (e) Economic; (f) Governance; (g) Health; (h) Institutional	Section 3.4
Physical vulnerability sub-dimensions	(a) Critical Infrastructure; (b) Environment; (c) General (urban) assets	Section 3.4
Data source	(a) Cadastral Data; (b) Census Data; (c) Field Monitoring Data; (d) Focus groups and Workshops; (e) Interviews, Surveys and Questionnaire Data; (f) Literature and Reports; (g) Maps and Topography; (h) modeled Data; (i) Remote Sensing Data	Section 3.5

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

3.1 Methodological approach used for assessing vulnerability

There is no universally agreed-upon typology for categorizing vulnerability assessment methods. For instance, Nasiri et al. (2016) identifies four quantitative method types: indicator-based approaches, vulnerability/damage curves, impact-data-based assessments, and model-based approaches, Hagenlocher et al. (2019) categorizes methods into index-based, dynamic simulation, and qualitative approaches, and Simmons et al. (2017) distinguishes between qualitative methods, quantitative indicator-based methods, and quantitative methods using statistical analyses or loss data to generate curves or trends. These distinctions reflect the underlying complexity of vulnerability. Indicator-based approaches typically aggregate a selection of factors influencing vulnerability into composite indices using various statistical methods such as weighting and normalization (e.g., Kumar and Bhattacharjya, 2020; de Brito et al., 2017; Moreira et al., 2021). Curve-based methods relate the intensity of the hazard (e.g., water depth, flood duration) to physical or monetary damage using empirical or modeled data, often called fragility-curves, loss-damage functions, or vulnerability curves (e.g., Dottori et al., 2016; Fuchs et al., 2019; Mechler and Bouwer, 2015). Qualitative approaches often draw on expert knowledge, case studies, or narrative frameworks to explore causal mechanisms and systemic effects (de Ruiter and van Loon, 2022; de Brito et al., 2024). Dynamic simulation models, such as agent-based or system dynamics modeling, capture the process of impact or change (e.g., Lu et al., 2023; Dzulkarnain et al., 2019; Joakim et al., 2016).

Based on our scoping review of 28 studies (see Appendix A), we developed a categorization scheme that builds on a combination of the aforementioned studies and includes an additional class for studies that do not focus on the assessment of vulnerability but address some of their components (e.g., economic resilience, behavioral patterns) (Table A1). This typology was used to classify all 67 relevant articles in our sample.

3.2 Conceptual focus of vulnerability assessments

In general, the concept of vulnerability can be approached through three complementary conceptualizations (Joakim et al., 2016, Figure 1). We follow the example of Jurgilevich et al. (2017) who use similar categories to differentiate between conceptual approaches to vulnerability: First, vulnerability can be seen as a precondition (*ex-ante*), referring to pre-existing sensitivities, structural deficits, or limited adaptive capacities that heighten the susceptibility to damage before a hazard occurs (Turner et al., 2003). This perspective emphasizes the underlying social, economic, and environmental conditions that result in uneven distribution of risk across society. Second, vulnerability can be conceptualized as a factor influencing how a hazard translates into actual impacts during the event itself (Cardona et al., 2012; Birkmann et al., 2013). Here, vulnerability alongside hazard and exposure as part of the risk equation shape the severity of losses. Third, vulnerability can be understood as an outcome (*ex-post*), highlighting the residual or newly emerging vulnerabilities that manifest after an event has taken place (O'BRIEN et al., 2007). This framing directs attention to how experiences of hazard and responses to it alter the vulnerability landscape over time.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

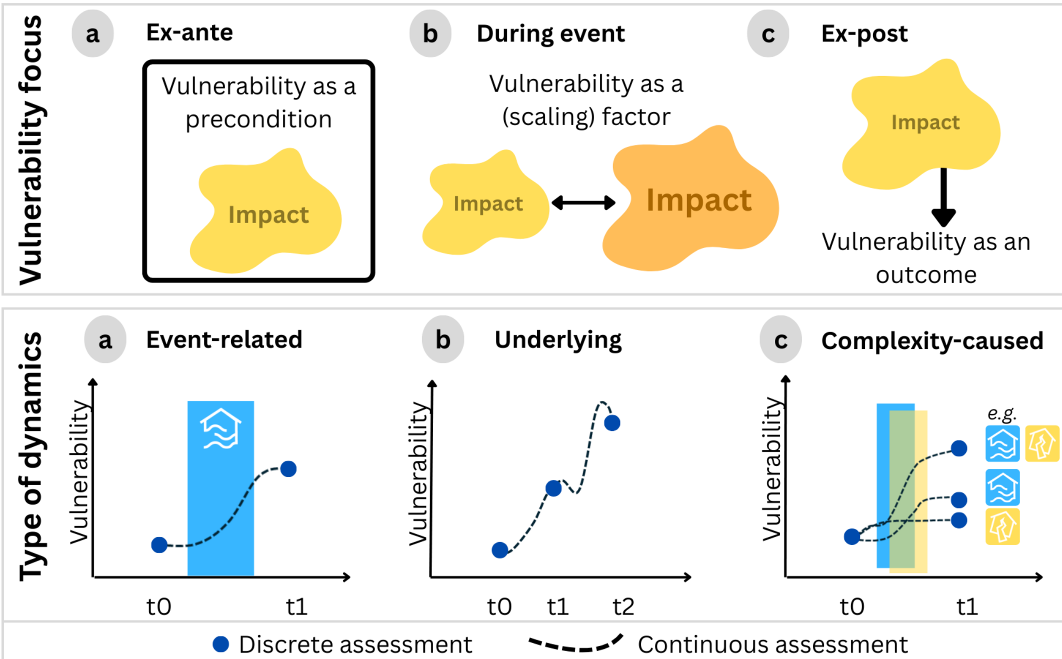

Figure 1. Top: Representation of the different categories to describe different conceptual foci of the vulnerability assessment. Bottom: Representation of the different types of dynamics. The temporal change in vulnerability can be assessed discretely or continuously.

3.3 Dynamic vulnerability types

We distinguish between the following types of dynamics (Figure 1: event-related dynamics, underlying dynamics, and complexity dynamics. Event-related dynamics focus on vulnerability dynamics regarding one specific event, usually comparing vulnerability before and after the event (e.g., vulnerability changes due to experienced flood event(s)). Underlying dynamics focus on how vulnerability changes at multiple points over an extended period, without explicit consideration of how multiple factors contribute to these changes. Complexity dynamics focuses on how vulnerability changes explicitly due to the joint effects of multiple factors.

We defined these types of dynamics, building on the typology proposed by de Ruiter and van Loon (2022). They differentiate between the following types: (1) vulnerability dynamics from underlying (non-hazard-specific) processes; (2) vulnerability dynamics from long-lasting disasters; and (3) vulnerability dynamics from compound or consecutive events. While we tested the use of these categories on the 28 scoping studies, they appeared to be poorly suited for distinguishing between different types of dynamics in the context of flood vulnerability. Only a very small share of studies in the scoping phase investigated vulnerability dynamics from long-lasting disasters (mostly related to the co-occurrence of the pandemic and flood events), which meant that respective studies were also categorized according to the above type (3), and the categories suggested by de Ruiter and van Loon (2022) did not account for the interaction of floods with other processes, such as spatial planning.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

3.4 Vulnerability dimensions

Although theoretical discussions provide essential insights into the meaning of vulnerability, empirical analysis requires a clear breakdown of how vulnerability is measured and structured in practice. We distinguish between two core dimensions: physical and social vulnerability. The physical dimension refers to the physical properties of elements at risk (Adger and Vincent, 2005; Cutter et al., 2000), whereas the social dimension refers to the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist, and recover from the impact of a flood (Wisner et al., 2004). Past studies have operationalised these dimensions in different ways, often drawing on earlier work without a clear rationale for the exact set of sub-dimensions. In this study, we adopt the approach by Stolte et al. (2024), which builds on commonly accepted categories from previous literature (e.g., Birkmann et al., 2013; Depietri, 2020; Hagenlocher et al., 2019) but adds explicit definitions to reduce ambiguity. This framework, shown in Table 2, ensures that the selected sub-dimensions remain distinct, comparable, and suited to our review's scope.

Table 2: Definition of sub-dimensions of vulnerability as proposed by Stolte et al. (2024)

Dimension	**Sub-dimension**	**Sub-dimension definition**
Physical	Critical Infrastructure	Characteristics of those physical assets in a city that are essential in maintaining business as usual. Drivers in this sub-dimension are, for instance, elevated roads, structural quality of bridges, and reliability of electricity networks.
	Environmental	Relates to the characteristics of (semi-)natural areas and phenomena in and around a city. Drivers in this sub-dimension are, for instance, the presence of urban vegetation and soil types.
	General Urban Assets	These are the characteristics of all the physical assets within a city that do not belong to the Environmental or Critical Infrastructure sub-dimensions. Drivers in this sub-dimension are, for instance, about building characteristics of mostly residential buildings (e.g., roof material, or the presence of a basement), the presence of emergency shelters, and urban form (i.e., the large-scale morphological characteristics of the urban area).
Social	Awareness & Information	This relates to personal awareness about hazards, as well as to information provisions about these hazards. Drivers in this sub-dimension are, for instance, about gathering/conveying information, risk perception, and preparedness.
	Crime & Conflict	Illegal activities and small to large-scale conflicts within the urban area. Drivers in this sub-dimension are, for instance, fear of crime, collaboration with gangs, and breaking regulations.
	Cultural & Behavior	Cultural beliefs and practices, as well as (culturally-influenced) behavior of citizens. Drivers in this sub-dimension, for instance, focus on health-affecting behaviors, social support, and adaptive behaviors.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Dimension	Sub-dimension	Sub-dimension definition
	Demographic	This refers to the demographic characteristics of the citizens in a city. Drivers in this sub-dimension include, for instance, age, education, and minority status.
	Economic	Related to the economy and economic system of a city. Drivers in this sub-dimension, for instance, are concerned with issues such as poverty, occupation, and insurance.
	Governance	Organization—but not the execution—of urban development. Drivers in this sub-dimension are, for instance, planning, empowerment, and (stakeholder) collaboration.
	Health	This refers to health, patients, and medical support in cities. Drivers in this sub-dimension, for instance, are concerned with pre-existing medical conditions, medical equipment, and water treatment.
	Institutional	The practical execution by institutions of what is determined by the urban authorities. Drivers in this sub-dimension are, for instance, about knowledge & expertise, resource allocation, and aid & intervention.

3.5 Input data for vulnerability assessments

A critical foundation of any vulnerability assessment is the type and quality of data on which it relies. The choice of input data not only determines the feasibility of applying different methods but also shapes the scope and validity of the results. Especially in the context of vulnerability indicators, there has been extensive discussion of the different data required and used to assess vulnerability (e.g., Papathoma-Köhle et al., 2017; Rufat et al., 2015; Tate, 2012), but with a limited comprehensive discussion of the respective data sources. Birkmann (2013) outline data needs and sources for the application of the Methods for the Improvement of Vulnerability Assessment (MOVE) framework, including micro-census, geodata, insurance information, statistical information of the city, and expert opinions. Kumar and Bhattacharjya (2020) offers a categorization between expert interviews, census data, survey-based questionnaires, satellite images, household surveys, field observations, official reports, and previous publications.

Based on the initial set of 28 studies, we found that the categorization by Kumar and Bhattacharjya (2020) was the most helpful as it captured the diversity of data sources more effectively (Table 1). We grouped some categories that seemed to have no implications for different methodological choices (e.g., official reports and previous publications) and complemented these with additional data sources commonly mentioned in the scoping studies (e.g., maps or cadastral data).

4 Results

We identified 67 relevant studies that explicitly consider dynamic vulnerability in their assessments. Figure 2 summarises the distribution of methodological approaches, conceptual foci, types of dynamics, physical and social vulnerability categories, and data sources considered. Overall, the main methodological approaches are relatively evenly represented. Most studies (n

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

= 42) address vulnerability dynamics as the outcome of a flood event. A smaller subset (n = 17) applies dynamic vulnerability in multiple ways, for example, treating it both as a precondition to hazard impact and as an outcome of the event. Across the sample, there is a modest bias toward event-related dynamics (n = 33), while complexity-related dynamics are least represented (n = 13).

In terms of vulnerability dimensions, several recur across multiple studies. Economic factors and cultural/behavioural aspects are most often considered, alongside awareness and information, demographic characteristics, and governance or institutional features. Most studies address multiple aspects of social vulnerability, while physical vulnerability dimensions are more narrowly represented. Here, there is a clear bias toward exposed urban assets (n = 38) and critical infrastructure (n = 21), which are often the sole physical characteristics analysed.

The reviewed studies employ a broad range of data sources, which are evenly distributed. Remote sensing data and workshop-derived inputs are the least common. Certain patterns emerge in the use of multiple data sources: cadastral and census data are frequently combined, often supplemented with modeled data, whereas interview data are less commonly integrated with other sources - likely because this form of data collection directly offers a combination of (self-reported) exposure and impact data, thus explanatory and outcome measures in one place.

In the following subsections, the results are presented per methodological approach.

4.1 Curve-based approaches

Fifteen studies apply curve-based methods to address dynamic vulnerability. As shown in Figure 2, the majority uses vulnerability as a factor influencing the degree of damage. All sources of vulnerability dynamics are represented relatively equally, while the considered subcomponents are biased toward the physical sub-dimension. Based on the conceptual focus of assessment and the types of dynamics, these studies can be grouped into five thematic clusters.

The first group comprises large-scale historical loss analyses (Formetta and Feyen, 2019; Jongman et al., 2012; Paprotny et al., 2025; Tanoue et al., 2016). These studies examine regional to global changes in vulnerability by comparing modeled hazard events with reported damages for the period between 1950 and 2020. Vulnerability is treated implicitly as a correction factor in the damage calculations. They combine modeled hazard and impact datasets with census and field monitoring data, alongside compiled damage reports. While Formetta and Feyen (2019); Jongman et al. (2012); Tanoue et al. (2016) primarily explore relationships between changes in losses and income development at the global scale, Paprotny et al. (2025) extend the analysis to include a spatio-temporal examination of drivers for flood protection and vulnerability in Europe. The earlier studies observe long-term declines in vulnerability linked to economic development, whereas Paprotny et al. (2025) identify a recent stabilisation and even slight increases in flood impacts since 2010. Formetta and Feyen (2019) also note that the relationship between wealth and vulnerability may be non-linear for the lowest income ranges, with initial increases in mortality and losses before eventual declines. Across these studies, limitations include the challenge of obtaining harmonized and reliable input data on experienced damages and losses, which affects spatially explicit conclusions, as well as a mismatch between reported and modeled damages, adding uncertainty to the attribution of vulnerability change (Formetta and Feyen, 2019; Paprotny et al., 2025).

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

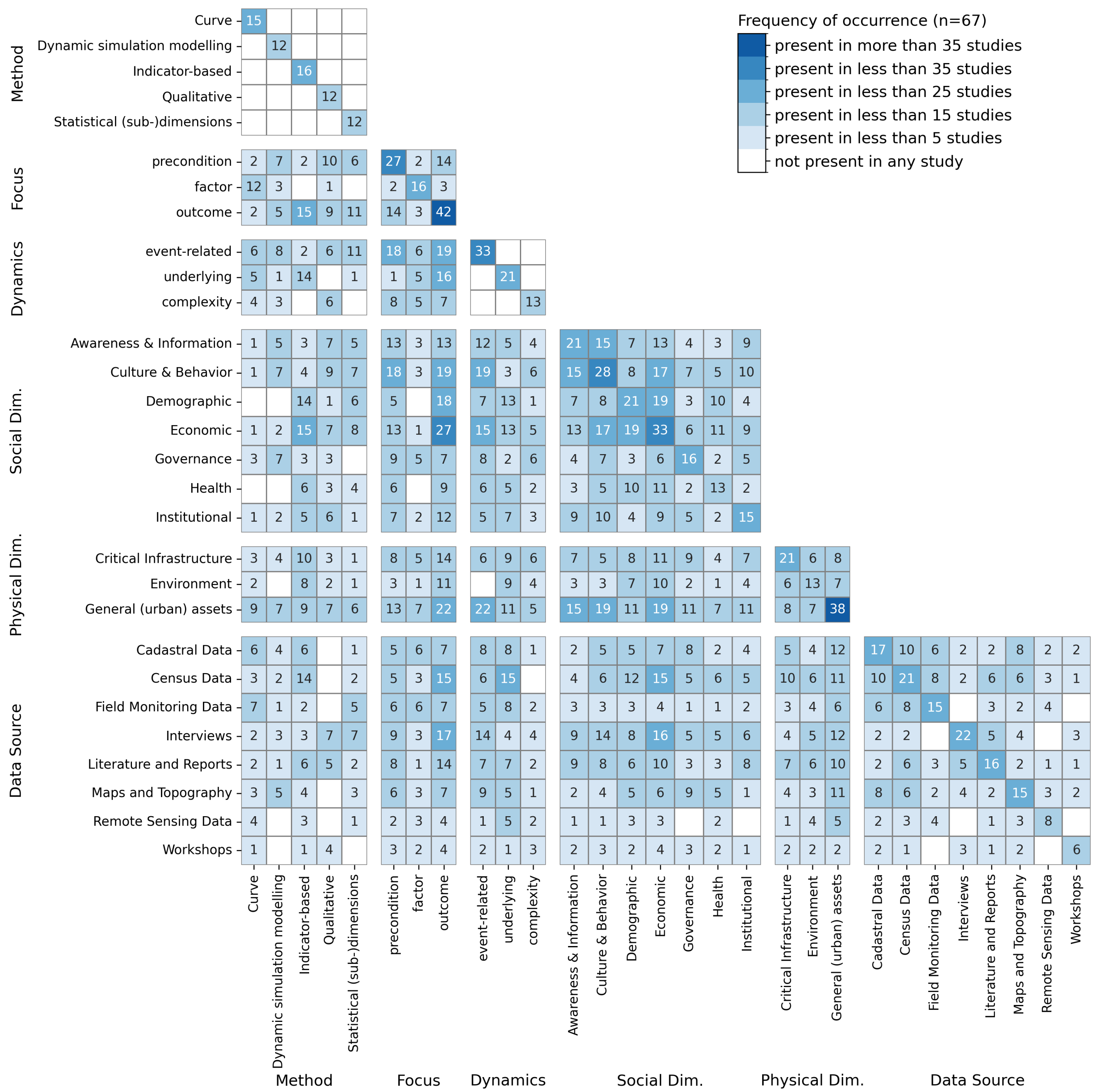

Figure 2. Summary of key characteristics of dynamic vulnerability assessment studies (n=67), including the main method applied, focus, dynamics type, the physical and social dimensions, and the type of data used. The heatmap shows the frequency of overlaps between different characteristics of studies, where each subplot represents a specific pair of categories (e.g., "Method" vs. "Focus").

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

A second group focuses on the local-scale evaluation of adaptation measures, such as dikes and retention basins (e.g., Arrighi et al., 2018; Bryant et al., 2022; Lasage et al., 2014; Schlumberger et al., 2022; Vamvakeridou-Lyroudia et al., 2020). While these measures primarily affect hazard or exposure, they also alter intrinsic characteristics of the exposed system through risk management interventions. These studies use statistical flood event data, cadastral and census records, and occasionally interviews or workshops to construct curves linking return periods with expected damages under different adaptation scenarios (Arrighi et al., 2018; Bryant et al., 2022; Vamvakeridou-Lyroudia et al., 2020) or linking different adaptation manifestations with expected damages for a representative flood event (Lasage et al., 2014). Commonly, these studies acknowledge the lack of calibration and validation data for the flood impact models.

The third group examined structural stability under multi-hazard loading of bridges, storage tanks, or coastal structures (Bernier and Padgett, 2019; Gehl and D'Ayala, 2018; van Verseveld et al., 2015). They employ various methods, including discrete Bayesian networks and physics-mechanistic models, to capture the effects of different load combinations on the element of interest. While Bernier and Padgett (2019) use statistical hazard data to determine the load combinations in a physics-mechanistic model for the analysis, van Verseveld et al. (2015) use damage data, modeled hazard data and property characteristics for the statistical inference of damages and Gehl and D'Ayala (2018) use scenarios of past flood events resulting in different scour depths, which affect the stability in case of earthquakes. Bernier and Padgett (2019) and van Verseveld et al. (2015) investigate the importance of considering multiple hazards to determine increased impacts (e.g., storage spill when considering load combinations) or improved predictability of damage by the model. Gehl and D'Ayala (2018) use a synthetic case to showcase how the performance loss exceedance probability is dependent on the combination of different hazard loads, and what implications it has for the recovery and restoration curves of the road network. We found similar studies to Gehl and D'Ayala (2018) which primarily focus on the bridge and its functionality loss due to a combination of flood-induced scour and earthquake damage (e.g., Pinto et al., 2024; Jithiya et al., 2022).

A fourth group explored crop and ecosystem vulnerability in relation to seasonal growth cycles. They investigate how seasonal hydrological variability and coupled extreme events influence the vegetation growth (Hong et al., 2025) or how growth cycles in combination with cultivation patterns result in spatio-temporal patterns of vulnerability (Sianturi et al., 2018). Both use the intrinsic information of growth-stage-related sensitivity as a precondition to estimate the vulnerability and impacts. Hong et al. (2025) use field observations and statistical methods to analyse growth responses to different sets of (multi-)hazard events, including single floods, droughts following floods, and floods following droughts. They derive impact curves and develop extreme-event-related growth response lags based on the statistical analysis of historical data. Sianturi et al. (2018) integrate crop growth-stage sensitivity with Earth observation imagery to capture spatio-temporal patterns of vulnerability evolution within the cultivation season in Indonesia. Limitations include Earth observation resolution constraints (Sianturi et al., 2018) and short time horizons that prevent consideration of multi-seasonal responses (Hong et al., 2025).

Finally, the remaining studies assess vulnerability dynamics as an outcome of specific events. Arrighi et al. (2022) develop curve relations between inundation depth and recovery time of cultural heritage sites using literature and reports. Yang et al. (2016) investigate the relationship between inundation depth and business recovery times through surveys, noting limitations due to small sample sizes and single-event focus.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

4.2 Dynamic simulation modelling approaches

Twelve studies employ dynamic simulation models. As shown in Figure 2, there is a slight bias in the conceptual focus towards vulnerability as a precondition, and only one out of the twelve studies addresses the underlying drivers of vulnerability dynamics.

The majority of studies use agent-based modelling approaches (ABM, Abebe et al., 2019; Ciullo et al., 2017; Dawson et al., 2011; Di Baldassarre et al., 2015; Erdlenbruch and Bonté, 2018; Haer et al., 2019; Jenkins et al., 2017; Sobiech, 2013). These models are primarily used to examine the effects of behavioural changes in response to flood events, such as shifts in risk perception, memory, and adaptation (i.e., the adoption of mitigation measures). For example, Di Baldassarre et al. (2015) capture the levee effect, increasing the long-term risk by encouraging development and population growth behind the dike. Haer et al. (2019) uses the ABM to derive information about the residual risk under different scenarios of adaptive behavior and Ciullo et al. (2017) investigate recovery time under different scenarios of adaptation strategies, risk attitude, and risk awareness. Only Sobiech (2013) and Erdlenbruch and Bonté (2018) calibrate agent behaviour using interview data, while most others rely on expert judgement or conceptual models from literature. Several studies applied ABMs to assess governance strategies, including the effectiveness of risk communication, early warning systems, and financial or technological incentives for risk mitigation (e.g., Abebe et al., 2019; Dawson et al., 2011; Erdlenbruch and Bonté, 2018; Haer et al., 2019; Jenkins et al., 2017). Erdlenbruch and Bonté (2018) is the only study investigating vulnerability dynamics from underlying processes, modelling the number of temporary adaptation measures implemented over time under varying lead times, lifetimes, and communication strategies. Across ABM studies, a recurring limitation is the lack of empirical data for parameterizing agent behavior, and a focus on select dynamics, which constrains model realism (e.g., Abebe et al., 2019; Ciullo et al., 2017; Haer et al., 2019).

Other simulation approaches include system dynamics modelling and complex computational models. Schoppa et al. (2024) use interview data to derive temporal relationships for awareness and preparedness, incorporating these into a system dynamics model for flood risk in Dresden. Batouli and Mostafavi (2018), Espinoza et al. (2016) and Kong et al. (2019) consider vulnerability dynamics due to a complex combination of processes. While Batouli and Mostafavi (2018) simulate temporal changes in infrastructure quality under combined effects of deterioration, flooding, and sea-level rise to test management strategies, Espinoza et al. (2016) and Kong et al. (2019) use a system-of-systems modelling approach to investigate interdependencies among infrastructure subsystems and their influence on cascading impacts and recovery. For example, Espinoza et al. (2016) (similar to Asaridis et al., 2025) build an impact model for an energy network accounting for the damage to individual elements using depth-damage curves, impact cascades through the energy network, the process (and time) for repair, and the effects of certain risk mitigation measures to reduce energy supply reductions. These studies often highlight limitations in capturing the full scope of complexity and dynamics, and identify the need for inclusion of additional processes in future work (e.g., Kong et al., 2019; Espinoza et al., 2016).

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

4.3 Indicator-based approaches

Indicator-based methods are applied in 16 studies, most often to investigate vulnerability dynamics as an outcome of underlying processes. Regarding the social dimension of vulnerability, the majority of studies primarily consider demographic and economic aspects, with an almost even distribution across the vulnerability components of the physical dimension.

Most studies calculate vulnerability indices at multiple points in time to capture underlying changes based on historical data (Cian et al., 2021; Chen and Chen, 2012; Alexander Fekete and Janos Bogardi, 2019; Garcia-Rosabel et al., 2024; He et al., 2024; Huang et al., 2024; Li, 2024; Meijer et al., 2023; Zhou et al., 2024) or projecting future changes (Giupponi et al., 2013; Jurgilevich, 2021). Census data is the most common source, but some studies integrate alternative datasets, such as field monitoring data on prior flood experiences (Cian et al., 2021), interview data for forward-looking vulnerability perspectives (Giupponi et al., 2013; Jurgilevich, 2021), maps and topographic data for identifying flood-prone areas (Meijer et al., 2023; Li, 2024), and Earth observation data for environmental sensitivity indicators (Cian et al., 2021). All studies reveal different patterns of changes in vulnerability and the reasons behind these changes. Often, they appear to be related to socio-economic changes, such as shifts in age distribution and employment patterns. The authors acknowledge a wide range of limitations, including the selection of parameters to form the indicators (e.g., Giupponi et al., 2013), uncertainty and lack of input data (e.g., Chen and Chen, 2012), focus on administrative boundaries (Zhou et al., 2025) and indicator weighting ambiguity (Li et al., 2021). Li et al. (2021) also acknowledges a limitation specific to dynamic vulnerability indicators, namely the chosen time gaps between moments of analysis (in their case, 10 years), which adds uncertainty regarding how the change in vulnerability occurred between the two moments of investigation.

Two studies (Ramesh et al., 2022; Khan and Salman, 2012) correlate pre-event vulnerability indicators with event impacts or post-event recovery trajectories. Ramesh et al. (2022) analyse emergency department visits following floods in relation to census-block vulnerability levels, and find that the number of emergency department visits increased with increasing vulnerability level post-flood overall and for some illnesses specifically. Khan and Salman (2012) explore recovery one year post-flood and its association with specific vulnerability sub-dimensions. They find correlations between livestock ownership (if livestock is owned, they are more likely to recover), adult literacy rates, and electricity access (the higher the access, the higher the chance of recovery).

4.4 Qualitative analysis

Thirteen studies use qualitative approaches. They either focus on event-related or complexity-driven vulnerability dynamics, and many studies approach vulnerability both as a precondition and an outcome (Figure 2). These studies primarily rely on participatory data collection, maps, and reports.

One group of studies investigates directional changes in vulnerability. Ajibade et al. (2013), Kreibich et al. (2017, 2023), Maiwald and Schwarz (2014), and Thieken et al. (2016) all examine changes in vulnerability as an outcome of specific flood events. Maiwald and Schwarz (2014) introduce an approach to change vulnerability class for buildings due to previous impacts based on expert judgement, Kreibich et al. (2017, 2023) and Thieken et al. (2016) use literature and reports about the existing

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

flood management system at consecutive (flood) events to investigate the directional change of vulnerability between the two events. Ajibade et al. (2013) focus specifically on the changes in vulnerability in the interaction of gender and other vulnerability characteristics using interviews and workshops for data collection (Ajibade et al., 2013). It is noteworthy that Kreibich et al. (2017, 2023), and Thieken et al. (2016) relate their analysis of vulnerability to consecutive hazard events and determine the changes in vulnerability based on the difference in experienced damages and reflections on the effectiveness of the risk management mechanism in place. As such, they also discuss measures taken in response to the first flood event that shape vulnerability as a precondition for the second event. Analysis of paired flood events by Kreibich et al. (2017, 2023) reveal general trends across four vulnerability dimensions: awareness, preparedness, emergency management, and coping capacity. They find that awareness often increases after flood events due to experience or public campaigns and that preparedness typically improves through better forecasting and early warning systems. They also find that emergency management structures improved in most cases, but coping capacity saw mixed results. Ajibade et al. (2013) find that middle and upper-class women are more protected from gender biases and the impacts of disaster. Lower-income women are more vulnerable after a flood due to limited economic resources and social support. Female-led households are particularly vulnerable after a flood.

Another group addresses complexity dynamics, often using narrative or storyline methods, primarily drawing on inputs from workshops and interviews, supplemented by literature and reports. Albulescu and Armaș (2024), de Bruijn et al. (2016), Rahman et al. (2021), Tran et al. (2022) and Whytlaw et al. (2021) investigate how multiple hazards or processes, such as floods coinciding with pandemics, repeated flood events alongside socio-economic change, or recovery of critical infrastructure, interact to influence vulnerability. Albulescu and Armaș (2024) use impact-chains to structure and manage the information on the complex processes. Rahaman and Esraz-Ul-Zannat (2021) use scenarios of co-occurring hazards (floods during extended periods of disease outbreaks) to collect inputs from residents regarding their perception of vulnerabilities and the effectiveness of different flood risk reduction measures. Chang et al. (2014) develop protocols for expert elicitation to estimate recovery patterns of critical infrastructure within two weeks following a flood event for a historic flood event and two augmented scenarios of counter-factual dike breach events. Multiple studies acknowledged the challenge of navigating the amount of information needed to explore the complexity of events, both in terms of visual representation and in the process of expert elicitation Albulescu and Armaș (2024); Chang et al. (2014).

4.5 Statistical analyses of vulnerability sub-dimensions

Twelve studies employ statistical approaches, which differ mainly in whether they analyse vulnerability as an outcome of events or as a precondition influencing outcomes. As shown in Figure 2, no study conceptualizes vulnerability as a factor in their analysis. In our sample set, we do not find any studies that investigate vulnerability dynamics due to the complexity of interacting processes. Instead, most studies employ an event-related assessment approach, utilizing various data sources and focusing on different vulnerability components. A key distinguishing element is whether they approached vulnerability solely as an outcome or as both a precondition and outcome.

The first group primarily applies an outcome-focused approach (Bubeck et al., 2012; Gallagher and Hartley, 2017; Kienzler et al., 2015; Köhler et al., 2023; Phifer et al., 1988). Bubeck et al. (2012), Kienzler et al. (2015) and Köhler et al. (2023)

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

investigate explicit correlations between past flood experiences and future flood preparedness or mitigation efforts, while Phifer et al. (1988) investigate relations to the health in the elderly and Gallagher and Hartley (2017) investigate debt patterns (regarding loans and credit cards) in the recovery process from flood events. Some studies rely primarily on interview data and apply descriptive statistical approaches in their analysis (Bubeck et al., 2012; Köhler et al., 2023; Phifer et al., 1988). Gallagher and Hartley (2017) use a difference-in-difference approach comparing census blocks that were affected by the flood with those that were not, using modeled flood data, census information, along with field monitoring data regarding the debt development. Phifer et al. (1988) find that flood vulnerability extends beyond immediate damage, as health effects persist over time, particularly among those who experience both personal and community-wide destruction. Similarly, Köhler et al. (2023) identify a paradox where individuals with more flood experience tend to take more precautionary measures but simultaneously feel less resilient. These findings underscore the role of psychological and social dynamics in vulnerability. While Bubeck et al. (2012) demonstrate that flood events trigger accelerated mitigation efforts and preparedness improvements, Kienzler et al. (2015) show that these improvements are inconsistent across cases. Gallagher and Hartley (2017) find that the debt decreased after an event in correlation with the payout of flood insurance money used to pay back loans instead of rebuilding. They hypothesize on possible reasons, both a demand-driven process (paying off loans and moving) and a lender-driven process (required to pay off mortgages on houses where house value was used as collateral). Similar to studies employing other methodological approaches, multiple studies acknowledge the challenges associated with input data completeness and accuracy (e.g., Gallagher and Hartley, 2017; Köhler et al., 2023). Bubeck et al. (2012) note some dynamic vulnerability specific challenges with regards to the timing of flood events considered, which is not resolved in enough detail to derive conclusions about overlapping processes of recovery and risk reduction/mitigation efforts.

Studies combining precondition–outcome perspectives include Atiqul Haq et al. (2024), Biswas et al. (2024), Jamshed et al. (2021), Jiang et al. (2023), Houston et al. (2021) and Salvucci and Santos (2020). These studies examine how flood exposure affects broader vulnerability characteristics, including fertility, birth weight, mobility, and consumption. They also investigate which vulnerability sub-dimensions are correlated with the changes. For example, Biswas et al. (2024) investigate which socio-economic factors are generally correlated more strongly with low birth weights in combination with potential flood exposure. Jamshed et al. (2021) investigate how the mobility patterns between rural and urban settlements varies depending on the age of the household head, economic situation, etc and Jiang et al. (2023) explore how recovery patterns in terms of credit use are affected by the wealth of the impacted household (Contreras and Torres-Machi, 2025, do the same for travel characteristics). They use various data sources for their analysis and apply some different methods of inference analysis including bivariate, multivariate or multinomial regression analysis (e.g., Atiqul Haq et al., 2024; Biswas et al., 2024; Jamshed et al., 2021), Autoregressive Integrated Moving Average model for time-series data (e.g., Atiqul Haq et al., 2024) and Moran's I statistics for spatial correlation analysis (e.g., Biswas et al., 2024), difference-in-difference to compare changes in affected regions in comparison to unaffected places (Salvucci and Tarp, 2021), and descriptive statistics (Jamshed et al., 2021; Jiang et al., 2023; Houston et al., 2021). Biswas et al. (2024) note that a key limitation in the inability to establish causality is due to input/measurement data constraints.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Tang et al. (2024) is the only study analysing changes in vulnerability due to underlying changes. They use random forests to classify different land use types and soil infiltration capacities, identifying the drivers that impact vegetation cover, infiltration capacity, and flood risk. They primarily rely on Earth observation data, complemented by local field measurements of infiltration capacity.

5 Discussion

This review set out to map and analyse how different flood vulnerability assessment methods are used to capture vulnerability dynamics. The analysis presented in the previous section provides an empirical basis for this comparison by synthesising 67 studies according to their methodological type, conceptual focus, and the types and dimensions of dynamics considered. Across the reviewed studies, dynamic vulnerability assessments served three primary purposes. First, they were used for policy analysis, providing accountability for past disaster risk management efforts and informing the design of future measures. Second, they contributed to understanding the effects of floods on vulnerability dimensions beyond direct damages, identifying changes that influence predisposition to harm and recovery capacity in future events. Third, they supported analyses of cascading impacts, recovery, and response patterns, particularly in infrastructure networks and socio-economic systems.

The methods varied in their capacity to address the three types of dynamics. Event-related dynamics were well represented across all methods, but were particularly prominent in curve-based, statistical, and many simulation studies. Underlying dynamics, such as demographic or economic shifts, were most systematically addressed in indicator-based analyses and in certain long-term curve-based studies. Complexity dynamics, involving multi-hazard interactions or cascading processes, were most extensively explored through simulation models, qualitative analyses, and mechanistic curve-based applications (e.g., structural stability under combined loads).

In the following, we will first reflect on the limitations of this study, and then discuss the relative strengths and limitations of each approach. Finally, we reflect on the opportunities and challenges for advancing dynamic vulnerability research.

5.1 Limitations of this study

While we categorized studies by their primary method, most applied mixed-methods designs. For example, Schoppa et al. (2024) used statistical methods to develop a model of risk awareness and memory, which was then implemented in a system dynamics model. Similarly, indicator-based studies often used statistical methods to explore correlations between vulnerability indicators and impacts, and curve-based studies frequently integrated statistical techniques to fit or validate curves. This methodological blending both enriches insights and complicates classification.

Another challenge emerged when categorizing by the conceptualization focus, as taken from Joakim et al. (2016). Particularly for studies investigating consecutive events or cascading impacts, vulnerability often acted simultaneously as a precondition and an outcome. This dual role blurs the boundaries between categories. It highlights the need for a more differentiated framework for categorizing the vulnerability focus in dynamic vulnerability research, especially in the context of multi-hazard events.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

The most significant limitation of our review lies in its design: it does not follow a fully systematic approach and is therefore not comprehensive. The choice of search terms, drawn primarily from the disaster risk research community, together with the applied definition of vulnerability and the focus on flood-related studies, may have introduced bias. However, the research field of dynamic vulnerability is still in its early stages (e.g., de Ruiter and van Loon, 2022). While our synthesis is partial, it provides a foundation for more systematic and comprehensive assessments that will become increasingly feasible as the field matures by sharpening the boundaries between different concepts and further advancing the methods used. We believe that this study offers insights into practical ways to categorize different studies based on their methodological approach, conceptual focus, and addressed dynamics, as well as inspiration for future research avenues and methodological advancements. It serves as a snapshot that can be used to build upon for more systematic studies that reach beyond the flood hazard research community or even beyond the disaster risk management community. In this study, we focus our review on flood-related vulnerability dynamics, but insights from research on vulnerability related to other natural hazards (e.g., earthquakes, droughts, or landslides) could be valuable inspiration for new methods applied to flood risk assessment (e.g., Cremen et al., 2022). It could be interesting for example, to investigate how hazards with different mechanistic understanding (e.g. earthquakes) or different time horizons (e.g. slow-onset events such as droughts) address the complexity of vulnerability dynamics, what methods they apply and data they use.

5.2 Method-level reflections and future research avenues

This review highlights a diverse range of methodological approaches applied to capture dynamic vulnerability in the context of flood risk. All five considered method types were capable of capturing aspects of vulnerability change, yet their patterns of use, strengths, and limitations varied considerably (Table 3).

Curve-based approaches were the most flexible, spanning all types of dynamics. Their strong link to quantitative impact modelling allowed predictive relationships between hazard intensity, exposure, and losses. Complexity dynamics were often captured through mechanistic modelling (e.g., structural failure, crop sensitivity), while event-driven change was frequently framed around adaptation measures. Future research could broaden the scope beyond governance interventions to processes such as infrastructure deterioration, long-term socio-economic change, or, in the context of crops and ecosystems, changes in vulnerability due to climate change, effects of invasive species, or other human interferences.

Dynamic simulation modelling approaches were primarily implemented as agent-based models. These excelled at representing behavioural feedbacks and governance processes. While often event-focused, they can also be adapted to explore gradual changes in vulnerability, particularly if parameterized with longitudinal social or behavioral data. Future work could focus on addressing the challenge of model calibration, for example, by incorporating studies that offer statistical insights into recovery patterns to reduce ambiguity or uncertainty in behavior dynamics. Agent-based modelling, in particular, is a promising methodological approach for combining multiple key concepts relevant for dynamic vulnerability and multi-hazard risk management, such as system-of-systems thinking and social processes of decision-making (Hochrainer-Stigler et al., 2023; de Ruiter and van Loon, 2022; Taberna et al., 2020).

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Table 3. Comparative overview of methodological approaches for assessing dynamic vulnerability in flood risk contexts.

Method type	Typical applications	Common limitations	Dynamics most often addressed
Curve-based approaches	Modelling hazard-impact relations over time; evaluation of adaptation measures; structural performance under multi-hazard loads; seasonal crop sensitivity; event-driven recovery analysis.	Limited calibration data; mismatch between modeled and reported damages; transferability across events; short temporal horizons.	All three types (event-related, underlying, complexity), strongest coverage across methods.
Dynamic simulation models	Agent-based models of behavioural change; governance strategy evaluation; system dynamics for risk perception and preparedness; system-of-systems infrastructure modelling.	High data requirements for parameterisation; resource-intensive; limited use for underlying long-term dynamics.	Primarily event-related and complexity dynamics; less focus on underlying dynamics.
Indicator-based approaches	Tracking socio-economic, demographic, and environmental vulnerability trends; projecting future vulnerability; linking indicators to recovery patterns.	Data scarcity for repeated measurements; parameter selection and weighting uncertainty; long intervals obscure processes.	Predominantly underlying dynamics; occasional event-related applications.
Qualitative methods	Directional change analysis between events; narrative exploration of multi-hazard interactions; participatory elicitation of recovery patterns and vulnerabilities.	Limited scalability; transferability issues; complexity management challenges.	Mostly complexity dynamics and event-related changes.
Statistical analyses	Correlating vulnerability subdimensions with outcomes; quasi-experimental impact assessments; trend analysis of specific social/economic indicators.	Dependent on available datasets; temporal and spatial resolution constraints; partial capture of system dynamics.	Primarily event-related dynamics; some underlying dynamics via trend analysis.

Indicator-based approaches effectively tracked underlying vulnerability changes, particularly socio-economic shifts. Although these approaches can link pre-event indicators to post-event impacts, their application to recovery processes remains underexplored. However, combining indicator-based assessments with statistical analyses could strengthen the linkage between pre-event vulnerability states and post-event outcomes, also offering evidence for refining curve-based models or calibrating simulation approaches. Future research could also focus on reducing the long intervals between observations. Such studies would potentially enable the development of temporal vulnerability curves that could be compared to those developed by,

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

for example, Jongman et al. (2012) or Tanoue et al. (2016), offering insights into the similarities and deviations in long-term vulnerability development using different methodological approaches.

Qualitative methods were primarily employed to investigate complexity dynamics or directional changes between consecutive events. They proved valuable in unpacking socio-political processes, contextual drivers, and interactions between multiple hazards, particularly where quantitative data were scarce. While the latter relied purely on reports and expert judgment, this approach might serve as inspiration for future studies, which could complement the analysis with simulation or curve-based assessment methods, for example, by comparing how buildings exposed to two consecutive floods experienced or reported damages differently. Similarly, qualitative methods could expand and further substantiate quantitative approaches to address aspects that are not captured by data or models. Future work could also focus on meta-analysis of qualitative narratives to identify recurring patterns that can inform modelling assumptions or indicator selection to capture vulnerability dynamics.

Lastly, **statistical analyses** were mainly applied within the context of specific events to correlate event experiences with changes in vulnerability or risk management. As such, they were pretty similar to indicator-based approaches in terms of conceptual focus. Their potential lies in expanding longitudinal coverage, which could help uncover the temporal evolution of recovery processes, as well as linking these processes with the impacts of subsequent events. Additionally, reflecting on how such statistical analysis could inform the formulation and calibration of potent dynamic simulation models or curve calibration could be a valuable exercise to utilize the limited available knowledge about recovery dynamics.

5.3 Key observations and implications across different methodological approaches

Across methodological types, scenarios were a central instrument for exploring vulnerability dynamics. They were used to evaluate disaster risk management options, test adaptation measures, or specify the characteristics of events under study. Emerging scenario frameworks, such as storyline approaches tailored to multi-hazard contexts (Crummy et al., in preparation), could help standardise scenario development or analysis for comparability across studies. Likewise, concepts from exploratory modelling and stress-testing (Marchau et al., 2019; Moallemi et al., 2020) could be adapted to identify critical thresholds and drivers of vulnerability change.

Another insight is that despite the diversity of methods and data sources, few studies explicitly identified causal pathways for changes in vulnerability. Most quantitative work focused on correlations, which provide associations but not mechanisms. Exceptions included mechanistic curve-based models of infrastructure or crop sensitivity, as well as specific dynamic simulation models. Qualitative approaches, such as the advanced impact chains developed by Albulescu and Armaș (2024) or expert elicitation by Whytlaw et al. (2021), offer more profound insight into process-level causality. A way forward may lie in meta-analyses of correlation studies to extract generalizable trends, analogous to how some depth–damage curves are developed for different infrastructure, thereby bridging qualitative process mapping with quantitative model calibration.

Finally, many limitations identified by the reviewed studies align with those commonly recognised for the respective methods. For curve-based approaches, issues such as lack of calibration, mismatch between modeled and observed losses, and limited transferability were frequently encountered (e.g., Dottori et al., 2016; Merz et al., 2010). Dynamic simulation models often struggled with parameterization and validation due to data scarcity (e.g. Taberna et al., 2020). Indicator approaches faced

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

challenges of repeated data collection, and weighting calibration (e.g., Moreira et al., 2021, 2023; Rufat et al., 2019). Qualitative methods were constrained by scalability and transferability (e.g., Denzin and Lincoln, 2011), while statistical approaches were limited by data resolution and temporal coverage (Merz et al., 2010).

In the context of dynamic vulnerability, these limitations appear to be intensified. More harmonized data are needed on multi-hazard events and other complex processes, as well as the processes that follow such events, particularly in terms of hazard, exposure, and vulnerability characteristics (Sakic Trogrlic et al., 2024). Repeated surveys, systematic monitoring, and the use of high-frequency remote sensing could help capture the temporal evolution of vulnerability more accurately, particularly for behavioural and social dimensions.

Similarly, for some of the studies, the timing is relevant: if events occur too closely together, recovery and preparedness processes can overlap, complicating attribution (Bubeck et al., 2012). Likewise, time lags in data collection can distort the picture of recovery and change (e.g., Albulescu and Armaș, 2024; Li et al., 2021; Houston et al., 2021). Future studies would benefit from systematically assessing the sensitivity of findings to the temporal relationship between data collection and events.

6 Conclusion

This review brought together and compared methodological applications that capture vulnerability dynamics in the context of flood risk. We focused on how common assessment methods have been used or adapted, the types of data and sub-dimensions considered, the conceptual focus on vulnerability, the nature of changes analyzed, and reported limitations. The aim was not to compile an exhaustive list of studies, but to provide a structured overview of different methods that can help researchers select and refine approaches, and to point to opportunities for applying these methods beyond flood risk to other hazards and thematic areas.

Across the 67 studies analyzed, we identified five main methodological approaches: curve-based, dynamic simulation, indicator-based, qualitative, and statistical, each with distinct strengths and limitations. Event-related dynamics dominate the field, with underlying and complexity-related changes receiving less attention. Social vulnerability dimensions such as economic, cultural/behavioural, and governance aspects are commonly included, while the physical dimension is often reduced to urban assets and critical infrastructure. Most methods draw on a combination of data sources, although remote sensing and workshop-derived inputs appear to be relatively uncommon.

Looking ahead, progress will depend on making better use of complementary strengths across methods, for example, by linking statistical trend analysis to simulation modelling, or combining qualitative narratives with curve-based estimates. More frequent and harmonised data collection would make it possible to study changes in vulnerability with greater precision. Furthermore, learning from other risk disciplines or research fields that investigate dynamic responses within a system may offer valuable insights to further advance research on vulnerability dynamics in the context of flood risk.

As the field develops, applying these approaches across various hazards, integrating different methods, paying closer attention to causal pathways, and conducting meta-analyses of findings regarding changes in vulnerability may improve both the understanding of vulnerability dynamics and the ability to manage and predict them.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Data availability. The list of reviewed publications and the dataset of the identified findings regarding the drivers and effects of dynamic vulnerability will be made available on Zenodo upon publication.

Author contributions. We use CRediT to distinguish authors' contributions. *Conceptualization*: PW (equal), MdR (equal), RST (equal). *Data Curation*: JS (lead). *Investigation*: AS (equal), HG (equal), JS (equal), MdB (equal), TS (equal), WJ (equal), AT (supporting), PW (supporting). *Methodology*: JS (lead), MdB (equal), AS (supporting), HG (supporting), TS (supporting), WJ (supporting). *Formal Analysis*: JS (lead), HG (equal), AS (equal), TS (equal), WJ (equal). *Visualization*: JS (lead), TS (supporting). *Writing – Original Draft*: HG (equal), JS (equal), MdB (equal), TS (equal), WJ (equal). *Writing – Review & Editing*: JS (lead), AS (equal), MdB (equal), PW (equal), TS (equal), HG (supporting), MdR (supporting), RST (supporting).

Competing interests. The authors have the following competing interests: Antonia Sebastian, Marleen de Ruiter, and Robert Šakić Trogrlić are editors of the Special Issue we are submitting this manuscript to. Also, Robert Šakić Trogrlić and Philip Ward are editors for NHESS.

Acknowledgements. JS, TS, WJ, PW, MCdR, and RST received support from the MYRIAD-EU project, which was funded by the European Union's Horizon 2020 research and innovation program under grant agreement No. 101003276. MCdR also received support from the Netherlands Organisation for Scientific Research (NWO) (VENI; grant no. VI.Veni.222.169). This work contributes to the goals of the IAHS scientific decade of HELPING (2023-2032). The authors acknowledge the use of generative AI (ChatGPT, Grammarly) in the preparation of this manuscript, specifically to support improvements in readability and language formulation. The authors take full responsibility for the content. JS wants to thank Sophie Buijs and Kelley de Polt for their feedback and ideas that helped to improve Figure 1.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Appendix A: Scoping Phase to identify example studies

Figure A1 highlights the process for conducting the scoping literature review. The review did not strictly adhere to specific protocols, similar to a semi-systematic literature review as defined by Snyder (2019) or a meta-narrative review as defined by Wong et al. (2013). A search query in Google Scholar on November 13, 2024, used keywords related to dynamic vulnerability and multi-hazard vulnerability assessment (Table A1). We also invited collaborators to suggest additional studies. This process yielded 980 publications.

Table A1. Overview of the applied search terms on Google Scholar and yielded results.

	N of publications
"dynamic vulnerability assessment" AND (flood OR floods OR flooding OR "flood event" OR “flood events” OR “floods”)	100
"multi-hazard vulnerability assessment" AND (flood OR floods OR flooding OR "flood event" OR “flood events” OR “floods”)	315
"multi-hazard vulnerability analysis" AND (flood OR floods OR flooding OR "flood event" OR “flood events” OR “floods”)	19
"dynamic vulnerability analysis" AND (flood OR floods OR flooding OR "flood event" OR “flood events” OR “floods”)	85
"vulnerability dynamics" AND (flood OR floods OR flooding OR "flood event" OR “flood events” OR “floods”)	419
Additional papers added by collaborators	41
Total	**980**

To be included, publications had to meet the following criteria: (i) published in English; (ii) peer-reviewed; (iii) freely accessible to the reviewers; (iv) investigate vulnerability concerning floods, potentially amongst other hazards; (v) adopt a definition of vulnerability consistent with the IPCC (2022) or UNDRR (2017) (see section 2); (vi) provide details on vulnerability assessment processes, data, and methodologies.

We first removed duplicates, inaccessible publications, and non-English or non-peer-reviewed works to identify relevant papers meeting these criteria. Next, we excluded irrelevant studies based on title and abstract. Finally, at least two authors reviewed each of the remaining publications for relevance. Decisions on their relevance were made collectively based on the inclusion criteria. Through this double-review process, 28 papers were identified as relevant, applying some form of dynamic vulnerability assessment in a specific case study. Due to the relatively small number of studies in each category, conducting meta-analyses or statistical comparisons was not feasible. Instead, we provide a qualitative description of key studies and their methodological approaches.

Table A2 shows how the reviewed studies were grouped into five main categories:

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

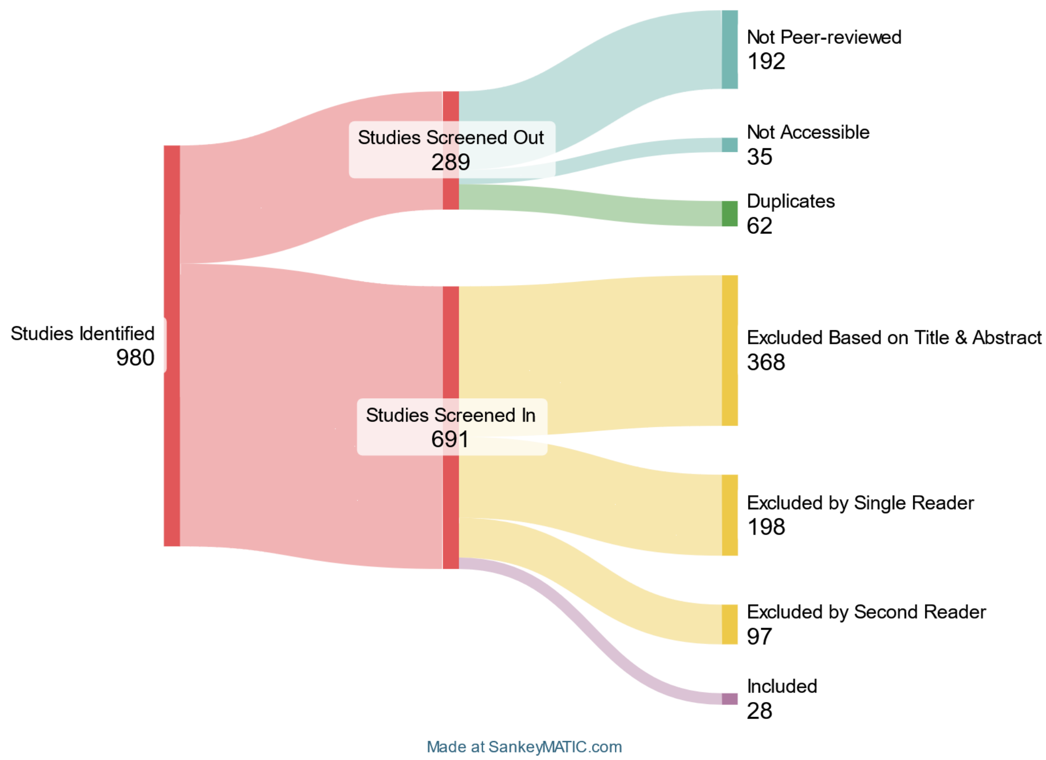

Figure A1. Summary of the literature review and number of publications included in this analysis.

Table A2. Grouping of initial scoping literature into methodological categories. Study reference numbers correspond to the full list in the Supplemental Information

Method Group	**initial method specification and publication**
Curve	multi-dimension fragility curve (3), impact/loss-based vulnerability curve (8, 11, 25), discrete Bayesian network (27)
Indicator	multi-hazard impact index (2), dynamic flood vulnerability index (6), Social vulnerability index (7, 18, 19), expert-based indicators (9)
dynamic simulation modelling	socio-hydrological method for continuous flood risk projection (23), agent-based model (24)
Qualitative	impact chain (1), expert inputs and report review (16, 17, 26, 28), scenario analysis (13), storyline (21)
Statistical	analysis of vulnerability sub-dimensions: Economic (10, 22), Cultural & Behavior (4, 11, 14), Awareness & Information (14, 15), Health (21), General Urban Assets (4)

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Appendix B: Search queries for Scopus search

Curve-based approaches

TITLE-ABS-KEY (("fragility curve*" OR "vulnerability curve*" OR "loss-damage function*" OR "damage curve*" OR "loss curve*" OR "impact function*" OR "damage function*") AND ("flood*" OR "flood risk" OR "flood damage") AND ("vulnerability" OR "resilience" OR "susceptibility") AND (("temporal" OR "dynamic*" OR "longitudinal" OR "time series" OR "change over time") OR ("recovery" OR "post-event" OR "adaptation")))

Dynamic simulation modelling approaches

TITLE-ABS-KEY ((("agent-based model*" OR "system dynamics model*" OR "dynamic simulation" OR "process-based model*" OR "socio-hydrological model*" OR "simulation model*") AND ("flood*" OR "flood risk") AND ("vulnerability" OR "resilience" OR "adaptive capacity")) AND (("temporal" OR "dynamic*" OR "longitudinal" OR "time series" OR "change over time") OR ("recovery" OR "post-event" OR "adaptation")))

Indicator-based approaches

TITLE-ABS-KEY(("vulnerability ind*" OR "impact ind*" OR "indicator-based approach*" OR "index-based approach*" OR "composite ind*" OR "index-based assessment*" OR "indicator-based assessment*") AND flood* AND ("vulnerability" OR "resilience" OR "coping capacity" OR "adaptive capacity") AND ("temporal*" OR "dynamic*" OR "longitudinal" OR "time series" OR "change over time" OR "recovery" OR "post-event"))

Qualitative approaches

TITLE-ABS-KEY ((("qualitative assessment*" OR "impact chain*" OR "expert judgment" OR "scenario analysis" OR "storyline approach*" OR "narrative analysis" OR "report review" OR "vulnerability matrix*") AND ("flood*" OR "flood risk") AND ("vulnerability" OR "resilience" OR "adaptive capacity")) AND (("temporal" OR "dynamic*" OR "longitudinal" OR "time series" OR "change over time") OR ("recovery" OR "post-event" OR "adaptation")))

Statistical analysis of vulnerability sub-components

ABS ("statistical analysis" OR "multivariate analysis" OR "regression analysis" OR "principal component analysis" OR "latent variable model*" OR "data-driven approach*" OR "trend analysis") AND TITLE-ABS ("flood*") AND ABS ("vulnerability" OR "resilience" OR "coping capacity" OR "adaptive capacity") AND ABS ("temporal*" OR "dynamic*" OR "longitudinal" OR "time series" OR "change over time" OR "recovery" OR "post-event")

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

References

Abebe, Y. A., Ghorbani, A., Nikolic, I., Vojinovic, Z., and Sanchez, A.: A coupled flood-agent-institution modelling (CLAIM) framework for urban flood risk management, Environmental Modelling & Software, 111, 483–492, https://doi.org/10.1016/j.envsoft.2018.10.015, 2019.

Adger, W. N. and Vincent, K.: Uncertainty in adaptive capacity, Comptes Rendus Geoscience, 337, 399–410, https://doi.org/10.1016/j.crte.2004.11.004, 2005.

Ahmed, M. A., Sridharan, B., Saha, N., Sannasiraj, S. A., and Kuiry, S. N.: Assessment of coastal vulnerability for extreme events, International Journal of Disaster Risk Reduction, 82, 103 341, https://doi.org/10.1016/j.ijdrr.2022.103341, 2022.

Ajibade, I., McBean, G., and Bezner-Kerr, R.: Urban flooding in Lagos, Nigeria: Patterns of vulnerability and resilience among women, Global Environmental Change, 23, 1714–1725, https://doi.org/10.1016/j.gloenvcha.2013.08.009, 2013.

Albulescu, A.-C. and Armaș, I.: An impact-chain-based exploration of multi-hazard vulnerability dynamics: the multi-hazard of floods and the COVID-19 pandemic in Romania, Natural Hazards and Earth System Sciences, 24, 2895–2922, https://doi.org/10.5194/nhess-24-2895-2024, 2024.

Alexander Fekete and Janos Bogardi: Resilience and Vulnerability: Conceptual revolution(s) or only revolving around words? A collection of essays, working papers and think pieces from the period 2008-2018, https://www.researchgate.net/profile/alexander-fekete/publication/337603951_resilience_and_vulnerability_conceptual_revolutions_or_only_revolving_around_words_a_collection_of_essays_working_papers_and_think_pieces_from_the_period_2008-2018, 2019.

Alwang, J., Siegel, P. B., and Jorgensen, S. L.: Vulnerability: a view from different disciplines, World Bank, Washington, DC, https://documents1.worldbank.org/curated/en/636921468765021121/pdf/multi0page.pdf, 2001.

Arrighi, C., Rossi, L., Trasforini, E., Rudari, R., Ferraris, L., Brugioni, M., Franceschini, S., and Castelli, F.: Quantification of flood risk mitigation benefits: A building-scale damage assessment through the RASOR platform, Journal of Environmental Management, 207, 92–104, https://doi.org/10.1016/j.jenvman.2017.11.017, 2018.

Arrighi, C., Carraresi, A., and Castelli, F.: Resilience of art cities to flood risk: A quantitative model based on depth–idleness correlation, Journal of Flood Risk Management, 15, https://doi.org/10.1111/jfr3.12794, 2022.

Asaridis, P., Molinari, D., Di Maio, F., Ballio, F., and Zio, E.: A probabilistic modeling and simulation framework for power grid flood risk assessment, International Journal of Disaster Risk Reduction, 120, 105 353, https://doi.org/10.1016/j.ijdrr.2025.105353, 2025.

Atiqul Haq, S. M., Chowdhury, M. A. B., Ahmed, K. J., and Uddin, M. J.: Effects of extreme climate events and child mortality on total fertility rate in Bangladesh, Heliyon, 10, e35 087, https://doi.org/10.1016/j.heliyon.2024.e35087, 2024.

Ballesteros, C. and Esteves, L. S.: Integrated Assessment of Coastal Exposure and Social Vulnerability to Coastal Hazards in East Africa, Estuaries and coasts : journal of the Estuarine Research Federation, 44, 2056–2072, https://doi.org/10.1007/s12237-021-00930-5, 2021.

Barendrecht, M. H., Matanó, A., Mendoza, H., Weesie, R., Rohse, M., Koehler, J., de Ruiter, M., Garcia, M., Mazzoleni, M., Aerts, J. C. J. H., Ward, P. J., Di Baldassarre, G., Day, R., and van Loon, A. F.: Exploring drought–to–flood interactions and dynamics: A global case review, Wiley Interdisciplinary Reviews: Water, 11, https://doi.org/10.1002/wat2.1726, 2024.

Barik, K. K., Mohanty, P. C., Nanda, S., Ramasamy, A., and Mahendra, R. S.: Earth Observation Technique-Based Coastal Vulnerability Assessment of Northern Odisha, East Coast of India, Journal of the Indian Society of Remote Sensing, 49, 293–303, https://doi.org/10.1007/s12524-020-01216-2, 2021.

Batouli, M. and Mostafavi, A.: Multiagent Simulation for Complex Adaptive Modeling of Road Infrastructure Resilience to Sea–Level Rise, Computer-Aided Civil and Infrastructure Engineering, 33, 393–410, https://doi.org/10.1111/mice.12348, 2018.

Begum, M. E. A., Hossain, M. I., and Mainuddin, M.: Climate change perceptions, determinants and impact of adaptation strategies on watermelon farmers in the saline coastal areas of Bangladesh, Letters in Spatial and Resource Sciences, 16, 1–31, https://doi.org/10.1007/s12076-022-00324-6, 2023.

Bera, R. and Maiti, R.: An assessment of coastal vulnerability using geospatial techniques, Environmental Earth Sciences, 80, 1–18, https://doi.org/10.1007/s12665-021-09616-4, 2021.

Bernier, C. and Padgett, J. E.: Neural Networks for Estimating Storm Surge Loads on Storage Tanks, ISBN 979-11-967125-0-1, https://doi.org/10.22725/ICASP13.015, 2019.

Birkmann, J.: Measuring vulnerability to natural hazards: towards disaster resilient societies, Measuring vulnerability to natural hazards: towards disaster resilient societies, 2013.

Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., Kienberger, S., Keiler, M., Alexander, D., Zeil, P., and Welle, T.: Framing vulnerability, risk and societal responses: the MOVE framework, Natural Hazards, 67, 193–211, https://doi.org/10.1007/s11069-013-0558-5, 2013.

Biswas, S., Mondal, S., Banerjee, A., Alam, A., and Satpati, L.: Investigating the association between floods and low birth weight in India: Using the geospatial approach, The Science of the total environment, 912, 169 593, https://doi.org/10.1016/j.scitotenv.2023.169593, 2024.

Bryant, S. P., Davies, E. G. R., Sol, D., and Davis, S.: The progression of flood risk in southern Alberta since the 2013 flood, Journal of Flood Risk Management, 15, e12 811, https://doi.org/10.1111/jfr3.12811, 2022.

Bubeck, P., Botzen, W. J. W., Kreibich, H., and Aerts, J. C. J. H.: Long-term development and effectiveness of private flood mitigation measures: an analysis for the German part of the river Rhine, Natural Hazards and Earth System Sciences, 12, 3507–3518, https://doi.org/10.5194/nhess-12-3507-2012, 2012.

Buijs, S. L., Sauer, I. J., Kropf, C. M., Juhel, S., Stalhandske, Z., and de Ruiter, M. C.: Recovery under consecutive disasters: how recovery dynamics shape societal resilience, https://doi.org/10.5194/egusphere-2025-3200, 2025.

Cardona, O.-D., van Aalst, M. K., Birkmann, J., Fordham, M., McGregor, G., Perez, R., Pulwarty, R. S., Schipper, E. L. F., Sinh, B. T., Décamps, H., Keim, M., Davis, I., Ebi, K. L., Lavell, A., Mechler, R., Murray, V., Pelling, M., Pohl, J., Smith, A.-O., and Thomalla, F.: Determinants of Risk: Exposure and Vulnerability, in: A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, edited by Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M. and Midgley, P.M., pp. 65–108, Cambridge University Press, Cambridge, UK, and New York, NY, USA, ISBN 978-1-107-02506-6, https://doi.org/10.1017/CBO9781139177245.005, 2012.

Carlier, B., Puissant, A., Dujarric, C., and Arnaud-Fassetta, G.: Upgrading of an index-oriented methodology for consequence analysis of natural hazards: application to the Upper Guil catchment (southern French Alps), Natural Hazards and Earth System Sciences, 18, 2221–2239, https://doi.org/10.5194/nhess-18-2221-2018, 2018.

Chang, S. E., McDaniels, T., Fox, J., Dhariwal, R., and Longstaff, H.: Toward disaster-resilient cities: characterizing resilience of infrastructure systems with expert judgments, Risk Analysis, 34, 416–434, https://doi.org/10.1111/risa.12133, 2014.

Chen, P. and Chen, X.: Spatio-temporal variation of flood vulnerability at the Poyang Lake Ecological Economic Zone, Jiangxi Province, China, Water Science and Technology, 65, 1332–1340, https://doi.org/10.2166/wst.2012.027, 2012.

Choong, J. J., Wagenaar, D., Rabonza, M. L., Hamel, P., Switzer, A. D., and Lallemant, D.: Shared hazards, unequal outcomes: income-driven inequities in disaster risk, npj Natural Hazards, 2, https://doi.org/10.1038/s44304-025-00087-2, 2025.

Cian, F., Giupponi, C., and Marconcini, M.: Integration of earth observation and census data for mapping a multi-temporal flood vulnerability index: a case study on Northeast Italy, Natural Hazards, 106, 2163–2184, https://doi.org/10.1007/s11069-021-04535-w, 2021.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Ciullo, A., Viglione, A., Castellarin, A., Crisci, M., and Di Baldassarre, G.: Socio-hydrological modelling of flood-risk dynamics: comparing the resilience of green and technological systems, Hydrological Sciences Journal, 62, 880–891, https://doi.org/10.1080/02626667.2016.1273527, 2017.

Contreras, F. and Torres-Machi, C.: Data-driven methodology to quantify traffic resilience of communities from crowdsourced location data, International Journal of Disaster Risk Reduction, 118, 105 219, https://doi.org/10.1016/j.ijdrr.2025.105219, 2025.

Cremen, G., Galasso, C., and McCloskey, J.: Modelling and quantifying tomorrow's risks from natural hazards, The Science of the total environment, 817, 152 552, https://doi.org/10.1016/j.scitotenv.2021.152552, 2022.

Cutter, S. L.: Vulnerability to environmental hazards, Progress in Human Geography, 20, 529–539, https://doi.org/10.1177/030913259602000407, 1996.

Cutter, S. L., Mitchell, J. T., and Scott, M. S.: Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina, Annals of the Association of American Geographers, 90, 713–737, https://doi.org/10.1111/0004-5608.00219, 2000.

Dawson, R. J., Peppe, R., and Wang, M.: An agent-based model for risk-based flood incident management, Natural Hazards, 59, 167–189, https://doi.org/10.1007/s11069-011-9745-4, 2011.

de Angeli, S., Malamud, B. D., Rossi, L., Taylor, F. E., Trasforini, E., and Rudari, R.: A multi-hazard framework for spatial-temporal impact analysis, International Journal of Disaster Risk Reduction, p. 102829, https://doi.org/10.1016/j.ijdrr.2022.102829, 2022.

de Brito, M. M., Evers, M., and Höllermann, B.: Prioritization of flood vulnerability, coping capacity and exposure indicators through the Delphi technique: A case study in Taquari-Antas basin, Brazil, International Journal of Disaster Risk Reduction, 24, 119–128, https://doi.org/10.1016/j.ijdrr.2017.05.027, 2017.

de Brito, M. M., Sodoge, J., Fekete, A., Hagenlocher, M., Koks, E., Kuhlicke, C., Messori, G., de Ruiter, M., Schweizer, P.-J., and Ward, P. J.: Uncovering the Dynamics of Multi–Sector Impacts of Hydrological Extremes: A Methods Overview, Earth's Future, 12, e2023EF003 906, https://doi.org/10.1029/2023EF003906, 2024.

de Bruijn, K. M., Cumiskey, L., Ní Dhubhda, R., Hounjet, M., and Hynes, W.: Flood vulnerability of critical infrastructure in Cork, Ireland, E3S Web of Conferences, 7, 07 005, https://doi.org/10.1051/e3sconf/20160707005, 2016.

de Ruiter, M. C. and van Loon, A. F.: The challenges of dynamic vulnerability and how to assess it, iScience, p. 104720, https://doi.org/10.1016/j.isci.2022.104720, 2022.

de Ruiter, M. C., Couasnon, A., Homberg, M. J. C., Daniell, J. E., Gill, J. C., and Ward, P. J.: Why We Can No Longer Ignore Consecutive Disasters, Earth's Future, 8, e2019EF001 425, https://doi.org/10.1029/2019EF001425, 2020.

Denzin, N. K. and Lincoln, Y. S.: The Sage handbook of qualitative research, SAGE, Thousand Oaks, 4th ed. edn., ISBN 9781412974172, 2011.

Depietri, Y.: The social–ecological dimension of vulnerability and risk to natural hazards, Sustainability Science, 15, 587–604, https://doi.org/10.1007/s11625-019-00710-y, 2020.

Di Baldassarre, G., Viglione, A., Carr, G., Kuil, L., Yan, K., Brandimarte, L., and Blöschl, G.: Debates-Perspectives on socio-hydrology: Capturing feedbacks between physical and social processes, Water Resources Research, 51, 4770–4781, https://doi.org/10.1002/2014WR016416, 2015.

Domeneghetti, A., Carisi, F., Castellarin, A., and Brath, A.: Evolution of flood risk over large areas: Quantitative assessment for the Po river, Journal of Hydrology, 527, 809–823, https://doi.org/10.1016/j.jhydrol.2015.05.043, 2015.

Dottori, F., Figueiredo, R., Martina, M. L. V., Molinari, D., and Scorzini, A. R.: INSYDE: a synthetic, probabilistic flood damage model based on explicit cost analysis, Natural Hazards and Earth System Sciences, 16, 2577–2591, https://doi.org/10.5194/nhess-16-2577-2016, 2016.

Douglas, J.: Physical vulnerability modelling in natural hazard risk assessment, Natural Hazards and Earth System Sciences, 7, 283–288, https://doi.org/10.5194/nhess-7-283-2007, 2007.

Drakes, O. and Tate, E.: Social vulnerability in a multi-hazard context: a systematic review, Environmental Research Letters, 17, 033 001, https://doi.org/10.1088/1748-9326/ac5140, 2022.

Dzulkarnain, A., Suryani, E., and Aprillya, M. R.: Analysis of Flood Identification and Mitigation for Disaster Preparedness: A System Thinking Approach, Procedia Computer Science, 161, 927–934, https://doi.org/10.1016/j.procs.2019.11.201, 2019.

Eakin, H. and Luers, A. L.: Assessing the Vulnerability of Social-Environmental Systems, Annual Review of Environment and Resources, 31, 365–394, https://doi.org/10.1146/annurev.energy.30.050504.144352, 2006.

Erdlenbruch, K. and Bonté, B.: Simulating the dynamics of individual adaptation to floods, Environmental Science & Policy, 84, 134–148, https://doi.org/10.1016/j.envsci.2018.03.005, 2018.

Espinoza, S., Panteli, M., Mancarella, P., and Rudnick, H.: Multi-phase assessment and adaptation of power systems resilience to natural hazards, Electric Power Systems Research, 136, 352–361, https://doi.org/10.1016/j.epsr.2016.03.019, 2016.

Fekete, A., Hufschmidt, G., and Kruse, S.: Benefits and Challenges of Resilience and Vulnerability for Disaster Risk Management, International Journal of Disaster Risk Science, 5, 3–20, https://doi.org/10.1007/s13753-014-0008-3, 2014.

Ford, J. D., Biesbroek, R., Ford, L. B., Creutzig, F., Haddaway, N., Harper, S., Minx, J. C., New, M., Sietsma, A. J., Zavaleta-Cortijo, C., and Callaghan, M.: Recommendations for producing knowledge syntheses to inform climate change assessments, Nature Climate Change, 15, 698–708, https://doi.org/10.1038/s41558-025-02354-6, 2025.

Formetta, G. and Feyen, L.: Empirical evidence of declining global vulnerability to climate-related hazards, Global environmental change : human and policy dimensions, 57, 101 920, https://doi.org/10.1016/j.gloenvcha.2019.05.004, 2019.

Fuchs, S., Birkmann, J., and Glade, T.: Vulnerability assessment in natural hazard and risk analysis: current approaches and future challenges, Natural Hazards, 64, 1969–1975, https://doi.org/10.1007/s11069-012-0352-9, 2012.

Fuchs, S., Keiler, M., Sokratov, S., and Shnyparkov, A.: Spatiotemporal dynamics: the need for an innovative approach in mountain hazard risk management, Natural Hazards, 68, 1217–1241, https://doi.org/10.1007/s11069-012-0508-7, 2013.

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

Gallagher, J. and Hartley, D.: Household Finance after a Natural Disaster: The Case of Hurricane Katrina, American Economic Journal: Economic Policy, 9, 199–228, https://doi.org/10.1257/pol.20140273, 2017.

Gallopín, G. C.: Linkages between vulnerability, resilience, and adaptive capacity, Global Environmental Change, 16, 293–303, https://doi.org/10.1016/j.gloenvcha.2006.02.004, 2006.

Garcia-Rosabel, S., Idowu, D., and Zhou, W.: At the Intersection of Flood Risk and Social Vulnerability: A Case Study of New Orleans, Louisiana, USA, GeoHazards, 5, 866–885, https://doi.org/10.3390/geohazards5030044, 2024.

Gehl, P. and D'Ayala, D.: System loss assessment of bridge networks accounting for multi-hazard interactions, Structure and Infrastructure Engineering, 14, 1355–1371, https://doi.org/10.1080/15732479.2018.1434671, 2018.

Giupponi, C., Borsuk, M. E., de Vries, B. J., and Hasselmann, K.: Innovative approaches to integrated global change modelling, Environmental Modelling & Software, 44, 1–9, https://doi.org/10.1016/j.envsoft.2013.01.013, 2013.

Haer, T., Botzen, W. J. W., and Aerts, J. C. J. H.: Advancing disaster policies by integrating dynamic adaptive behaviour in risk assessments using an agent-based modelling approach, Environmental Research Letters, 14, 044 022, https://doi.org/10.1088/1748-9326/ab0770, 2019.

Hagenlocher, M., Meza, I., Anderson, C. C., Min, A., Renaud, F. G., Walz, Y., Siebert, S., and Sebesvari, Z.: Drought vulnerability and risk assessments: state of the art, persistent gaps, and research agenda, Environmental Research Letters, 14, 083 002, https://doi.org/10.1088/1748-9326/ab225d, 2019.

Handmer, J. W., Dovers, S., and Downing, T. E.: Societal Vulnerability to Climate Change and Variability, Mitigation and Adaptation Strategies for Global Change, 4, 267–281, https://doi.org/10.1023/A:1009611621048, 1999.

Hastuti, A. W., Nagai, M., and Suniada, K. I.: Coastal Vulnerability Assessment of Bali Province, Indonesia Using Remote Sensing and GIS Approaches, Remote Sensing, 14, 4409, https://doi.org/10.3390/rs14174409, 2022.

He, X., Fang, Y., Wang, B., and Huang, X.: Towards a verifiable, uncertainty-controlled assessment of the spatiotemporal dynamics of social vulnerability to flash floods, Ecological Indicators, 166, 112 323, https://doi.org/10.1016/j.ecolind.2024.112323, 2024.

Herslund, L. B., Jalayer, F., Jean-Baptiste, N., Jørgensen, G., Kabisch, S., Kombe, W., Lindley, S., Nyed, P. K., Pauleit, S., Printz, A., and Vedeld, T.: A multi-dimensional assessment of urban vulnerability to climate change in Sub-Saharan Africa, Natural Hazards, 82, 149–172, https://doi.org/10.1007/s11069-015-1856-x, 2016.

Hinkel, J., Feyen, L., Hemer, M., Le Cozannet, G., Lincke, D., Marcos, M., Mentaschi, L., Merkens, J. L., de Moel, H., Muis, S., Nicholls, R. J., Vafeidis, A. T., van de Wal, R. S. W., Vousdoukas, M. I., Wahl, T., Ward, P. J., and Wolff, C.: Uncertainty and Bias in Global to Regional Scale Assessments of Current and Future Coastal Flood Risk, Earth's Future, 9, e2020EF001 882, https://doi.org/10.1029/2020EF001882, 2021.

Hochrainer-Stigler, S., Trogrlić Šakić, R., Reiter, K., Ward, P. J., de Ruiter, M. C., Duncan, M. J., Torresan, S., Ciurean, R., Mysiak, J., Stuparu, D., and Gottardo, S.: Toward a framework for systemic multi-hazard and multi-risk assessment and management, iScience, 26, 106 736, https://doi.org/10.1016/j.isci.2023.106736, 2023.

Hong, G., Xie, X., Tan, C., Liang, S., Hu, X., and Wu, X.: Assessment of vegetation vulnerability in floodplain wetlands: A perspective from carryover effect of seasonal growth under various extreme hydrological scenarios, Journal of Hydrology, 651, 132 622, https://doi.org/10.1016/j.jhydrol.2024.132622, 2025.

Hoque, M. A.-A., Ahmed, N., Pradhan, B., and Roy, S.: Assessment of coastal vulnerability to multi-hazardous events using geospatial techniques along the eastern coast of Bangladesh, Ocean & Coastal Management, 181, 104 898, https://doi.org/10.1016/j.ocecoaman.2019.104898, 2019.

Houston, D., Werritty, A., Ball, T., and Black, A.: Environmental vulnerability and resilience: Social differentiation in short– and long–term flood impacts, Transactions of the Institute of British Geographers, 46, 102–119, https://doi.org/10.1111/tran.12408, 2021.

Hsieh, H.-F. and Shannon, S. E.: Three approaches to qualitative content analysis, Qualitative health research, 15, 1277–1288, https://doi.org/10.1177/1049732305276687, 2005.

Huang, X., Li, J., Xu, H., Liao, B., Gu, H., Chen, Y., Ji, C., Zhang, B., and Du, S.: The changing social vulnerability in Shanghai during 2000–2020 and its implications for risk management, International Journal of Disaster Risk Reduction, 113, 104 852, https://doi.org/10.1016/j.ijdrr.2024.104852, 2024.

IPCC: Annex II: Glossary, in: Climate Change 2022 – Impacts, Adaptation and Vulnerability, edited by Pörtner, H.-O., Roberts, D. C., Tignor, M., Poloczanska, E. S., Mintenbeck, K., Alegría, A., Craig, M., Langsdorf, S., Löschke, S., Möller, V., Okem, A., and Rama, B., pp. 2897–2930, Cambridge University Press, ISBN 9781009325844, https://doi.org/10.1017/9781009325844.029, 2022.

Islam, M. K., Hasan, M., Rahman, M., Fayyaz, R., Chowdhury, M., and Hamid, T.: Shoreline Dynamics Assessment of Moheshkhali Island of Bangladesh using Integrated GIS-DSAS Techniques, The Dhaka University Journal of Earth and Environmental Sciences, 11, 1–14, https://doi.org/10.3329/dujees.v11i1.63707, 2023.

Jamshed, A., Birkmann, J., McMillan, J. M., Rana, I. A., Feldmeyer, D., and Sauter, H.: How do rural-urban linkages change after an extreme flood event? Empirical evidence from rural communities in Pakistan, The Science of the total environment, 750, 141 462, https://doi.org/10.1016/j.scitotenv.2020.141462, 2021.

Jenkins, K., Surminski, S., Hall, J., and Crick, F.: Assessing surface water flood risk and management strategies under future climate change: Insights from an Agent-Based Model, Science of The Total Environment, 595, 159–168, https://doi.org/10.1016/j.scitotenv.2017.03.242, 2017.

Jiang, Y., Yuan, F., Farahmand, H., Acharya, K., Zhang, J., and Mostafavi, A.: Data-driven tracking of the bounce-back path after disasters: Critical milestones of population activity recovery and their spatial inequality, International Journal of Disaster Risk Reduction, 92, 103 693, https://doi.org/10.1016/j.ijdrr.2023.103693, 2023.

Jithiya, K. K., Pandikkadavath, M. S., Mangalathu, S., and Nagarajan, P.: Seismic Mainshock—Aftershock (MS-AS) Vulnerability Assessment of Reinforced Concrete Bridge Exposed to Flood Induced Scour, in: Recent Advances in Earthquake Engineering, edited by Kolathayar, S. and Chian, S. C., vol. 175 of *Lecture Notes in Civil Engineering*, pp. 211–221, Springer Singapore, Singapore, ISBN 978-981-16-4616-4, https://doi.org/10.1007/978-981-16-4617-1_17, 2022.

Joakim, E. P., Mortsch, L., Oulahen, G., Harford, D., Klein, Y., Damude, K., and Tang, K.: Using system dynamics to model social vulnerability and resilience to coastal hazards, International Journal of Emergency Management, 12, 366, https://doi.org/10.1504/IJEM.2016.079846, 2016.

Jongman, B., Ward, P. J., and Aerts, J. C.: Global exposure to river and coastal flooding: Long term trends and changes, Global Environmental Change, 22, 823–835, https://doi.org/10.1016/j.gloenvcha.2012.07.004, 2012.

Jurgilevich, A.: Governance modes and epistemologies of future-oriented vulnerability assessments: Example of a mixed-methods approach, Futures, 128, 102 717, https://doi.org/10.1016/j.futures.2021.102717, 2021.

Jurgilevich, A., Räsänen, A., Groundstroem, F., and Juhola, S.: A systematic review of dynamics in climate risk and vulnerability assessments, Environmental Research Letters, 12, 013 002, https://doi.org/10.1088/1748-9326/aa5508, 2017.

Kantamaneni, K., Phillips, M., Thomas, T., and Jenkins, R.: Assessing coastal vulnerability: Development of a combined physical and economic index, Ocean & Coastal Management, 158, 164–175, https://doi.org/10.1016/j.ocecoaman.2018.03.039, 2018.

Khan, F. A. and Salman, A.: A simple human vulnerability index to climate change hazards for Pakistan, International Journal of Disaster Risk Science, 3, 163–176, https://doi.org/10.1007/s13753-012-0017-z, 2012.

Kienzler, S., Pech, I., Kreibich, H., Müller, M., and Thieken, A. H.: 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, 2015.

Köhler, L., Masson, T., Köhler, S., and Kuhlicke, C.: Better prepared but less resilient: the paradoxical impact of frequent flood experience on adaptive behavior and resilience, Natural Hazards and Earth System Sciences, 23, 2787–2806, https://doi.org/10.5194/nhess-23-2787-2023, 2023.

Kong, J., Simonovic, S. P., and Zhang, C.: Resilience Assessment of Interdependent Infrastructure Systems: A Case Study Based on Different Response Strategies, Sustainability, 11, 6552, https://doi.org/10.3390/su11236552, 2019.

Kreibich, H., Di Baldassarre, G., Vorogushyn, S., Aerts, J. C. J. H., Apel, H., Aronica, G. T., Arnbjerg-Nielsen, K., Bouwer, L. M., Bubeck, P., Caloiero, T., Chinh, D. T., Cortès, M., Gain, A. K., Giampá, V., Kuhlicke, C., Kundzewicz, Z. W., Llasat, M. C., Mård, J., Matczak, P., Mazzoleni, M., Molinari, D., Dung, N. V., Petrucci, O., Schröter, K., Slager, K., Thieken, A. H., Ward, P. J., and Merz, B.: Adaptation to flood risk: Results of international paired flood event studies, Earth's Future, 5, 953–965, https://doi.org/10.1002/2017EF000606, 2017.

Kreibich, H., Schröter, K., Di Baldassarre, G., van Loon, A. F., Mazzoleni, M., Abeshu, G. W., Agafonova, S., AghaKouchak, A., Aksoy, H., Alvarez-Garreton, C., Aznar, B., Balkhi, L., Barendrecht, M. H., Biancamaria, S., Bos-Burgering, L., Bradley, C., Budiyono, Y., Buytaert, W., Capewell, L., Carlson, H., Cavus, Y., Couasnon, A., Coxon, G., Daliakopoulos, I., de Ruiter, M. C., Delus, C., Erfurt, M., Esposito, G., François, D., Frappart, F., Freer, J., Frolova, N., Gain, A. K., Grillakis, M., Grima, J. O., Guzmán, D. A., Huning, L. S., Ionita, M., Kharlamov, M., Khoi, D. N., Kieboom, N., Kireeva, M., Koutroulis, A., Lavado-Casimiro, W., Li, H.-Y., Llasat, M. C., Macdonald, D., Mård, J., Mathew-Richards, H., McKenzie, A., Mejia, A., Mendiondo, E. M., Mens, M., Mobini, S., Mohor, G. S., Nagavciuc, V., Ngo-Duc, T., Nguyen, H. T. T., Nhi, P. T. T., Petrucci, O., Quan, N. H., Quintana-Seguí, P., Razavi, S., Ridolfi, E., Riegel, J., Sadik, M. S., Sairam, N., Savelli, E., Sazonov, A., Sharma, S., Sörensen, J., Souza, F. A. A., Stahl, K., Steinhausen, M., Stoelzle, M., Szalińska, W., Tang, Q., Tian, F., Tokarczyk, T., Tovar, C., van Tran, T. T., van Huijgevoort, M. H. J., van Vliet, M. T. H., Vorogushyn, S., Wagener, T., Wang, Y., Wendt, D. E., Wickham, E., Yang, L., Zambrano-Bigiarini, M., and Ward, P. J.: Panta Rhei benchmark dataset: socio-hydrological data of paired events of floods and droughts, Earth System Science Data, 15, 2009–2023, https://doi.org/10.5194/essd-15-2009-2023, 2023.

Ku, H., Kim, T., and Song, Y.-i.: Coastal vulnerability assessment of sea-level rise associated with typhoon-induced surges in South Korea, Ocean & Coastal Management, 213, 105 884, https://doi.org/10.1016/j.ocecoaman.2021.105884, 2021.

Kumar, D. and Bhattacharjya, R. K.: Review of different methods and techniques used for flood vulnerability analysis, https://doi.org/10.5194/nhess-2020-297, 2020.

Lasage, R., Veldkamp, T. I. E., de Moel, H., Van, T. C., Phi, H. L., Vellinga, P., and Aerts, J. C. J. H.: Assessment of the effectiveness of flood adaptation strategies for HCMC, Natural Hazards and Earth System Sciences, 14, 1441–1457, https://doi.org/10.5194/nhess-14-1441-2014, 2014.

Li, X.: Measuring social vulnerability to natural hazards in China: a modified index approach, Population and Environment, 46, 1–27, https://doi.org/10.1007/s11111-024-00455-6, 2024.

Li, Y., Gong, S., Zhang, Z., Liu, M., Sun, C., and Zhao, Y.: Vulnerability evaluation of rainstorm disaster based on ESA conceptual framework: A case study of Liaoning province, China, Sustainable Cities and Society, 64, 102 540, https://doi.org/10.1016/j.scs.2020.102540, 2021.

Londe, L. d. R., Santos, L. B. L., Soriano, E., Tomas, L. R., and Carvalho, T.: Urban mobility data to support the assessment of dynamic vulnerability to disasters, in: 2015 2nd International Conference on Information and Communication Technologies for Disaster Management (ICT-DM), IEEE, https://doi.org/10.1109/ict-dm.2015.7402036, 2015.

Lu, Y., Wang, Y., and Zhang, L.: System dynamic modeling of the NGO post-disaster relief contribution in the 2021 Henan flood in China, International Journal of Disaster Risk Reduction, 89, 103 626, https://doi.org/10.1016/j.ijdrr.2023.103626, 2023.

Maiwald, H. and Schwarz, J.: Schadensmodelle für extreme Hochwasser – Teil 2: Erste Schlussfolgerungen aus dem Ereignis vom Juni 2013, Bautechnik, 91, 354–367, https://doi.org/10.1002/bate.201300102, 2014.

Marchau, V. A. W. J., Walker, W. E., Bloemen, P. J. T. M., and Popper, S. W., eds.: Decision Making under Deep Uncertainty: From Theory to Practice, Springer eBook Collection, Springer International Publishing, Cham, ISBN 9783030052522, https://doi.org/10.1007/978-3-030-05252-2, 2019.

Matanó, A., de Ruiter, M. C., Koehler, J., Ward, P. J., and van Loon, A. F.: Caught Between Extremes: Understanding Human–Water Interactions During Drought–To–Flood Events in the Horn of Africa, Earth's Future, 10, e2022EF002 747, https://doi.org/10.1029/2022EF002747, 2022.

Mazzorana, B., Levaggi, L., Keiler, M., and Fuchs, S.: Towards dynamics in flood risk assessment, Natural Hazards and Earth System Sciences, 12, 3571–3587, https://doi.org/10.5194/nhess-12-3571-2012, 2012.

Mechler, R. and Bouwer, L. M.: Understanding trends and projections of disaster losses and climate change: is vulnerability the missing link?, Climatic Change, 133, 23–35, https://doi.org/10.1007/s10584-014-1141-0, 2015.

Meijer, L. G., Reimann, L., and Aerts, J.: Comparing spatially explicit approaches to assess social vulnerability dynamics to flooding, International Journal of Disaster Risk Reduction, 96, 103 883, https://doi.org/10.1016/j.ijdrr.2023.103883, 2023.

Merz, B., Kreibich, H., Schwarze, R., and Thieken, A.: 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, 2010.

Miguez, M. G. and Veról, A. P.: A catchment scale Integrated Flood Resilience Index to support decision making in urban flood control design, Environment and Planning B: Urban Analytics and City Science, 44, 925–946, https://doi.org/10.1177/0265813516655799, 2017.

Miller, F., Osbahr, H., Boyd, E., Thomalla, F., Bharwani, S., Ziervogel, G., Walker, B., Birkmann, J., van der Leeuw, S., Rockström, J., Hinkel, J., Downing, T., Folke, C., and Nelson, D.: Resilience and Vulnerability: Complementary or Conflicting Concepts?, Ecology and Society, 15, https://doi.org/10.5751/ES-03378-150311, 2010.

Moallemi, E. A., Kwakkel, J., de Haan, F. J., and Bryan, B. A.: Exploratory modeling for analyzing coupled human-natural systems under uncertainty, Global Environmental Change, 65, 102 186, https://doi.org/10.1016/j.gloenvcha.2020.102186, 2020.

Moreira, L. L., de Brito, M. M., and Kobiyama, M.: Review article: A systematic review and future prospects of flood vulnerability indices, Natural Hazards and Earth System Sciences, 21, 1513–1530, https://doi.org/10.5194/nhess-21-1513-2021, 2021.

Moreira, L. L., Vanelli, F. M., Schwamback, D., Kobiyama, M., and de Brito, M. M.: Sensitivity analysis of indicator weights for the construction of flood vulnerability indexes: A participatory approach, Frontiers in Water, 5, https://doi.org/10.3389/frwa.2023.970469, 2023.

Moret, W.: Vulnerability assessment methodologies: A review of the literature, https://www.fhi360.org/wp-content/uploads/drupal/documents/vulnerability%20assessment%20literature%20review.pdf, 2014.

Nasiri, H., Mohd Yusof, M. J., and Mohammad Ali, T. A.: An overview to flood vulnerability assessment methods, Sustainable Water Resources Management, 2, 331–336, https://doi.org/10.1007/s40899-016-0051-x, 2016.

O'BRIEN, K., Eriksen, S., NYGAARD, L. P., and SCHJOLDEN, A. N.: Why different interpretations of vulnerability matter in climate change discourses, Climate Policy, 7, 73–88, https://doi.org/10.1080/14693062.2007.9685639, 2007.

Papathoma-Köhle, M., Gems, B., Sturm, M., and Fuchs, S.: Matrices, curves and indicators: A review of approaches to assess physical vulnerability to debris flows, Earth-Science Reviews, 171, 272–288, https://doi.org/10.1016/j.earscirev.2017.06.007, 2017.

Paprotny, D., 't Hart, C. M. P., and Morales-Nápoles, O.: Evolution of flood protection levels and flood vulnerability in Europe since 1950 estimated with vine-copula models, Natural Hazards, 121, 6155–6184, https://doi.org/10.1007/s11069-024-07039-5, 2025.

Petzold, J., Andrews, N., Ford, J. D., Hedemann, C., and Postigo, J. C.: Indigenous knowledge on climate change adaptation: a global evidence map of academic literature, Environmental Research Letters, 15, 113 007, https://doi.org/10.1088/1748-9326/abb330, 2020.

Phifer, J. F., Kaniasty, K. Z., and Norris, F. H.: The Impact of Natural Disaster on the Health of Older Adults: A Multiwave Prospective Study, Journal of Health and Social Behavior, 29, 65, https://doi.org/10.2307/2137181, 1988.

Pinto, F., Astroza, R., Pizarro, A., Bazáez, R., and Hernández, F.: Seismic fragility analysis of simply supported bridges considering uncertainty in scour condition, Structures, 64, 106 570, https://doi.org/10.1016/j.istruc.2024.106570, 2024.

Rahaman, M. and Esraz-Ul-Zannat, M.: Evaluating the impacts of major cyclonic catastrophes in coastal Bangladesh using geospatial techniques, SN Applied Sciences, 3, 1–21, https://doi.org/10.1007/s42452-021-04700-7, 2021.

Rahman, M. A., Dawes, L., Donehue, P., and Rahman, M. R.: Cross-temporal analysis of disaster vulnerability of the southwest coastal communities in Bangladesh, Regional Environmental Change, 21, 1–13, https://doi.org/10.1007/s10113-021-01797-9, 2021.

Ramesh, B., Jagger, M. A., Zaitchik, B., Kolivras, K. N., Swarup, S., Deanes, L., Hallisey, E., Sharpe, J. D., and Gohlke, J. M.: Flooding and emergency department visits: Effect modification by the CDC/ATSDR Social Vulnerability Index, International Journal of Disaster Risk Reduction, 76, https://doi.org/10.1016/j.ijdrr.2022.102986, 2022.

Rentschler, J., Salhab, M., and Jafino, B. A.: Flood exposure and poverty in 188 countries, Nature Communications, 13, 3527, https://doi.org/10.1038/s41467-022-30727-4, 2022.

Rufat, S., Tate, E., Burton, C. G., and Maroof, A. S.: Social vulnerability to floods: Review of case studies and implications for measurement, International Journal of Disaster Risk Reduction, 14, 470–486, https://doi.org/10.1016/j.ijdrr.2015.09.013, 2015.

Rufat, S., Tate, E., Emrich, C. T., and Antolini, F.: How valid are social vulnerability models?, Annals of the American Association of Geographers, 109, 1131–1153, https://doi.org/10.1080/24694452.2018.1535887, 2019.

Sakic Trogrlic, R., Reiter, K., Ciurean, R., Gottardo, S., Torresan, S., Daloz, A. S., Ma, L., Padron-Fumero, N., Tatman, S., and Ward, P.: Challenges in Assessing and Managing Multi-Hazard Risks: A European Stakeholders' Perspective, Copernicus GmbH, https://doi.org/10.5194/egusphere-egu24-3843, 2024.

Salvucci, V. and Santos, R.: Vulnerability to Natural Shocks: Assessing the Short-Term Impact on Consumption and Poverty of the 2015 Flood in Mozambique, Ecological Economics, 176, 106 713, https://doi.org/10.1016/j.ecolecon.2020.106713, 2020.

Salvucci, V. and Tarp, F.: Estimating poverty transitions in Mozambique using synthetic panels: A validation exercise and an application to cross-sectional survey data, https://doi.org/10.35188/UNU-WIDER/2021/964-8, 2021.

Sauer, I. J., Mester, B., Frieler, K., Zimmermann, S., Schewe, J., and Otto, C.: Limited progress in global reduction of vulnerability to flood impacts over the past two decades, Communications Earth & Environment, 5, https://doi.org/10.1038/s43247-024-01401-y, 2024.

Schlumberger, J., Ferrarin, C., Jonkman, S. N., Diaz Loaiza, M. A., Antonini, A., and Fatorić, S.: Developing a framework for the assessment of current and future flood risk in Venice, Italy, Natural Hazards and Earth System Sciences, 22, 2381–2400, https://doi.org/10.5194/nhess-22-2381-2022, 2022.

Schoppa, L., Barendrecht, M. H., Paprotny, D., Sairam, N., Sieg, T., and Kreibich, H.: Projecting Flood Risk Dynamics for Effective Long–Term Adaptation, Earth's Future, 12, e2022EF003 258, https://doi.org/10.1029/2022EF003258, 2024.

Schröter, K., Kreibich, H., Vogel, K., Riggelsen, C., Scherbaum, F., and Merz, B.: How useful are complex flood damage models?, Water Resources Research, 50, 3378–3395, https://doi.org/10.1002/2013WR014396, 2014.

Sianturi, R., Jetten, V. G., and Sartohadi, J.: Mapping cropping patterns in irrigated rice fields in West Java: Towards mapping vulnerability to flooding using time-series MODIS imageries, International Journal of Applied Earth Observation and Geoinformation, 66, 1–13, https://doi.org/10.1016/j.jag.2017.10.013, 2018.

Simmons, D. C., Corbane, C., Menoni, S., Schneiderbauer, S., and Zschau, J.: Understanding disaster risk: risk assessment methodologies and examples, in: Science for Disaster Risk Management 2017: knowing better and loosing less, edited by Poljansek, K., Marin Ferrer, M., de Groeve, T., and Clark, I., p. Chapter 2, Publications Office of the European Union, Luxembourg, ISBN 978-92-79-60678-6, 2017.

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., van Aalst, M., Totin, E., and Trisos, C. H.: A framework for complex climate change risk assessment, One Earth, 4, 489–501, https://doi.org/10.1016/j.oneear.2021.03.005, 2021.

Snyder, H.: Literature review as a research methodology: An overview and guidelines, Journal of Business Research, 104, 333–339, https://doi.org/10.1016/j.jbusres.2019.07.039, 2019.

Sobiech, C.: Theoretical Research Framework, Agent-Based Simulation of Vulnerability Dynamics, pp. 31–73, https://doi.org/10.1007/978-3-642-32365-2_3, 2013.

Spielman, S. E., Tuccillo, J., Folch, D. C., Schweikert, A., Davies, R., Wood, N., and Tate, E.: Evaluating social vulnerability indicators: criteria and their application to the Social Vulnerability Index, Natural Hazards, 100, 417–436, https://doi.org/10.1007/s11069-019-03820-z, 2020.

Stolte, T. R., Koks, E. E., de Moel, H., Reimann, L., van Vliet, J., de Ruiter, M. C., and Ward, P. J.: VulneraCity–drivers and dynamics of urban vulnerability based on a global systematic literature review, International Journal of Disaster Risk Reduction, 108, 104 535, https://doi.org/10.1016/j.ijdrr.2024.104535, 2024.

Taberna, A., Filatova, T., Roy, D., and Noll, B.: Tracing resilience, social dynamics and behavioral change: a review of agent-based flood risk models, 2663-3027, https://opus.lib.uts.edu.au/handle/10453/146588, 2020.

Tang, J., Liu, D., Shang, C., and Niu, J.: Impacts of land use change on surface infiltration capacity and urban flood risk in a representative karst mountain city over the last two decades, Journal of cleaner production, 454, 142 196, https://doi.org/10.1016/j.jclepro.2024.142196, 2024.

Tanoue, M., Hirabayashi, Y., and Ikeuchi, H.: Global-scale river flood vulnerability in the last 50 years, Scientific Reports, 6, 36 021, https://doi.org/10.1038/srep36021, 2016.

Tate, E.: Social vulnerability indices: a comparative assessment using uncertainty and sensitivity analysis, Natural Hazards, 63, 325–347, https://doi.org/10.1007/s11069-012-0152-2, 2012.

Tellman, B., Sullivan, J. A., Kuhn, C., Kettner, A. J., Doyle, C. S., Brakenridge, G. R., Erickson, T. A., and Slayback, D. A.: Satellite imaging reveals increased proportion of population exposed to floods, Nature, 596, 80–86, https://doi.org/10.1038/s41586-021-03695-w, 2021.

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

Thomson, H., Zeff, H. B., Kleiman, R., Sebastian, A., and Characklis, G. W.: Systemic Financial Risk Arising from Residential Flood Losses, Earth's Future, 11, e2022EF003 206, https://doi.org/10.1029/2022EF003206, 2023.

Tran, T. A., Rigg, J., Taylor, D., Miller, M. A., Pittock, J., and Le, P. T.: Social Memory in the Mekong's Changing Floodscapes: Narratives of Agrarian Communities' Adaptation, Human ecology: an interdisciplinary journal, 50, 879–893, https://doi.org/10.1007/s10745-022-00362-0, 2022.

Turner, B. L., Kasperson, R. E., Matson, P. A., McCarthy, J. J., Corell, R. W., Christensen, L., Eckley, N., Kasperson, J. X., Luers, A., Martello, M. L., Polsky, C., Pulsipher, A., and Schiller, A.: A framework for vulnerability analysis in sustainability science, Proceedings of the National Academy of Sciences of the United States of America, 100, 8074–8079, https://doi.org/10.1073/pnas.1231335100, 2003.

UNDRR: Terminology, https://www.undrr.org/terminology/, 2017.

https://doi.org/10.5194/egusphere-2025-6132
Preprint. Discussion started: 8 January 2026

Vamvakeridou-Lyroudia, L. S., Chen, A. S., Khoury, M., Gibson, M. J., Kostaridis, A., Stewart, D., Wood, M., Djordjevic, S., and Savic, D. A.: Assessing and visualising hazard impacts to enhance the resilience of Critical Infrastructures to urban flooding, The Science of the total environment, 707, 136 078, https://doi.org/10.1016/j.scitotenv.2019.136078, 2020.

van Loenhout, J. and McClean, D.: The human cost of disasters: an overview of the last 20 years (2000-2019), https://www.undrr.org/publication/human-cost-disasters-overview-last-20-years-2000-2019, 2020.

van Verseveld, H., van Dongeren, A. R., Plant, N. G., Jäger, W. S., and den Heijer, C.: Modelling multi-hazard hurricane damages on an urbanized coast with a Bayesian Network approach, Coastal Engineering, 103, 1–14, https://doi.org/10.1016/j.coastaleng.2015.05.006, 2015.

Ward, P. J., Blauhut, V., Bloemendaal, N., Daniell, J. E., de Ruiter, M. C., Duncan, M. J., Emberson, R., Jenkins, S. F., Kirschbaum, D., Kunz, M., Mohr, S., Muis, S., Riddell, G. A., Schäfer, A., Stanley, T., Veldkamp, T. I. E., and Winsemius, H. C.: Review article: Natural hazard risk assessments at the global scale, Natural Hazards and Earth System Sciences, 20, 1069–1096, https://doi.org/10.5194/nhess-20-1069-2020, 2020a.

Ward, P. J., de Ruiter, M. C., Mård, J., Schröter, K., van Loon, A., Veldkamp, T., von Uexkull, N., Wanders, N., AghaKouchak, A., Arnbjerg-Nielsen, K., Capewell, L., Carmen Llasat, M., Day, R., Dewals, B., Di Baldassarre, G., Huning, L. S., Kreibich, H., Mazzoleni, M., Savelli, E., Teutschbein, C., van den Berg, H., van der Heijden, A., Vincken, J. M., Waterloo, M. J., and Wens, M.: The need to integrate flood and drought disaster risk reduction strategies, Water Security, 11, 100 070, https://doi.org/10.1016/j.wasec.2020.100070, 2020b.

Ward, P. J., Daniell, J., Duncan, M., Dunne, A., Hananel, C., Hochrainer-Stigler, S., Tijssen, A., Torresan, S., Ciurean, R., Gill, J. C., Sillmann, J., Couasnon, A., Koks, E., Padrón-Fumero, N., Tatman, S., Tronstad Lund, M., Adesiyun, A., Aerts, J. C. J. H., Alabaster, A., Bulder, B., Campillo Torres, C., Critto, A., Hernández-Martín, R., Machado, M., Mysiak, J., Orth, R., Palomino Antolín, I., Petrescu, E.-C., Reichstein, M., Tiggeloven, T., van Loon, A. F., Vuong Pham, H., and de Ruiter, M. C.: Invited perspectives: A research agenda towards disaster risk management pathways in multi-(hazard-)risk assessment, Natural Hazards and Earth System Sciences, 22, 1487–1497, https://doi.org/10.5194/nhess-22-1487-2022, 2022.

Whytlaw, J. L., Hutton, N., Wie Yusuf, J.-E., Richardson, T., Hill, S., Olanrewaju-Lasisi, T., Antwi-Nimarko, P., Landaeta, E., and Diaz, R.: Changing vulnerability for hurricane evacuation during a pandemic: Issues and anticipated responses in the early days of the COVID-19 pandemic, International journal of disaster risk reduction : IJDRR, 61, 102 386, https://doi.org/10.1016/j.ijdrr.2021.102386, 2021.

Wisner, B., Blaikie, P., Cannon, T., and Davis, I.: At risk: Natural hazards, people's vulnerability, and disasters, Routledge, London and New York, 2nd ed. edn., ISBN 9780415252164, 2004.

Wong, G., Greenhalgh, T., Westhorp, G., Buckingham, J., and Pawson, R.: RAMESES publication standards: meta-narrative reviews, BMC medicine, 11, 20, https://doi.org/10.1186/1741-7015-11-20, 2013.

Yang, L., Kajitani, Y., Tatano, H., and Jiang, X.: A methodology for estimating business interruption loss caused by flood disasters: insights from business surveys after Tokai Heavy Rain in Japan, Natural Hazards, 84, 411–430, https://doi.org/10.1007/s11069-016-2534-3, 2016.

Zhou, M., He, Q., Gu, Y., Wang, K., and Shen, Z.: Urban Flood Resilience Assessment of Prefecture-Level Cities in Yangtze River Delta, ISPRS International Journal of Geo-Information, 14, 108, https://doi.org/10.3390/ijgi14030108, 2025.

Zhou, Z., Guo, Y., Chen, D., Li, K., Wang, R., Wei, X., Zhang, J., Zhao, C., Tong, Z., and Liu, X.: Identification and Spatiotemporal Characteristic Analysis of Compound Weather and Climate Extremes for Maize in Different Climate Zones of the Songliao Plain, International Journal of Disaster Risk Science, 15, 831–851, https://doi.org/10.1007/s13753-024-00585-3, 2024.