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Review article: A systematic review and future prospects of flood vulnerability indices

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Abstract. This paper provides a state-of-art account on flood vulnerability indices, highlighting worldwide trends and future research directions. A total of 95 peer-reviewed articles published between 2002-2019 were systematically analyzed. An exponential rise in research effort is demonstrated, with 80% of the articles being published since 2015. The majority of these studies (62.1%) focused on the neighborhood followed by the city scale (14.7%). Min-max normalization (30.5%), equal weighting (24.2%), and linear aggregation (80.0%) were the most common methods. With regard to the indicators used, a focus was given to socio-economic aspects (e.g. population density, illiteracy rate, gender), whilst components associated with the citizen's coping and adaptive capacity were slightly covered. Gaps in current research include a lack of sensitivity and uncertainty analyzes (present in only 9.5% and 3.2% of papers, respectively); inadequate or inexistent validation of the results (present in 13.7% of the studies); lack of transparency regarding the rationale for weighting and indicator selection; and use of static approaches, disregarding temporal dynamics. We discuss the challenges associated with these findings for the assessment of flood vulnerability and provide a research agenda for attending to these gaps.

1 Introduction

Floods affect billions of people worldwide (Zarekarizi et al., 2020). Indeed, according to the Emergency Events Database (CRED, 2019), around 50,000 people died and approximately 10% of the world population was affected by floods between 2009 and 2019. Due to population growth and climate change, more frequent and widespread floods are anticipated (Hirsch and Archfield, 2015; Leung et al., 2019). Therefore, flood risk management is required for mitigating potential damages.

Nowadays there is a consensus that risk (i.e. the potential for adverse impacts), is not driven solely by natural hazards (e.g. floods, droughts), but depends on the interactions between hazards, exposure, and vulnerability (IPCC, 2012, 2014). In this regard, vulnerability plays an important, yet still neglected, role in flood risk assessment. Based on it, the social, economic, physical, cultural, environmental and institutional dimensions of a system exposed to natural hazards are taken into account (Birkmann et al., 2013). Due to its importance, the need to understand and assess flood vulnerability has been highlighted by international initiatives such as the Sendai Framework for Disaster Risk Reduction 2015–2030 (UNISDR 2015).

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In response to this, numerous studies have been undertaken to better understand flood vulnerability. Nevertheless, both the terminology and methodology used in these assessments are still a subject of discussion (Aroca-Jiménez et al., 2020). In fact, some consider vulnerability as a function of exposure and susceptibility (Balica et al., 2009; IPCC, 2001; Turner et al., 2003; UNDP, 2014), while others separate these concepts (Dilley et al., 2005; Fedeski and Gwilliam, 2007), as it is possible to be exposed to a hazard and not to be vulnerable. For instance, a person may live in an area prone to natural hazards, but have sufficient alternatives to modify the structure of his house to prevent potential losses (Cardona et al., 2012). Here, we consider vulnerability as the physical, social, economic, and environmental conditions and coping capacities, which increase the susceptibility of the exposed elements to the impact of hazards (UNISDR, 2009). Exposure, on the other hand, is defined as a situation where people, infrastructure, housing, industrial facilities, and other human resources are located in hazard-prone areas (UNISDR, 2016).

A wide range of approaches exists for assessing flood vulnerability. The most commonly used methods are: stage-damage functions (Papathoma-Köhle et al., 2012, 2017; Tarbotton et al., 2015); damage matrices (Bründl et al., 2009; Papathoma-Köhle et al., 2017); and vulnerability indices (Birkmann, 2006; de Brito et al., 2017; Kappes et al., 2012; Moreira et al., 2021). The first two methods assess only the physical vulnerability, neglecting the social vulnerability of their inhabitants (Koks et al., 2015). However, the capacity of households to cope, adapt and respond to hazards is equally important to assess the potential impacts of floods (de Brito et al., 2018). Therefore, given the importance of holistic studies on vulnerability to ensure better representation of reality, the use of vulnerability indices is recommended (Balica et al., 2013; Birkmann et al., 2013; Fuchs et al., 2011; Nasiri et al., 2016). Indices serve as a summary of complex and multidimensional issues to assist decision-makers, to facilitate the interpretation of a phenomenon, to increase public interest through a summary of the results. Flood vulnerability indices are, therefore, a tool to measure the vulnerability degree throughout the aggregation of several indicators or variables. Despite their advantages, indices can present misleading messages if they are poorly constructed or misinterpreted. Hence, a clear understanding of the normalization, weighting and aggregation methods used to build an index is required (Moreira et al., 2021).

Over the past years, a number of review articles about flood vulnerability have been published. For instance, Rufat et al. (2015) reviewed 67 articles to identify the leading drivers of social vulnerability to floods. Nasiri et al. (2016) compared several methods, including damage-curves, computer modeling and indicators to evaluate flood vulnerability. Similarly, Rehman et al. (2019) and Fatemi et al. (2017) reviewed different methodologies used for assessing flood vulnerability. Jurgilevich et al. (2017) systematically reviewed 42 climate risk and vulnerability assessments. More recently, Diaz-Sarachaga and Jato-Espino (2020) evaluated 72 articles related to the appraisal of vulnerability to different types of hazards in urban areas.

Notwithstanding these advances, to the best of our knowledge, no study has conducted a systematic review of flood vulnerability indices with a focus on the different stages involved in the construction of flood vulnerability indices. The investigation of the methods used for normalizing, weighting, aggregation and validation and the implications for each choice for vulnerability assessment has received little attention so far. In addition, the temporal dynamics of flood vulnerability has not been tackled by the existing reviews. This is particularly important given that certain adaptation policies and strategies

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may reduce short-term risk probability, but increase long-term vulnerability and exposure (Cardona et al., 2012). Therefore, a better understanding of the methods used in each step of the index construction, temporal dynamics (e.g., pre and post-event flood indicators), the uncertainty involved and validation is needed for advancing research on flood vulnerability assessment. Considering the aforementioned gaps and given the proliferation of methods for building vulnerability indices, it is pertinent to review the development of this field. Hence, here, we carried out a systematic literature review of indices used to assess flood vulnerability. A focus is given to urban and riverine floods. The following questions guided the analysis: (1) Which spatial scale was considered? (2) Which indicators were most commonly used to measure flood vulnerability? (3) How were the temporal dynamics of vulnerability addressed (e.g. pre or post-flood event)? (4) Which methods were most commonly applied in each stage of the index building process (i.e. normalization, weighting, aggregation)? (5) To which extent did these studies conduct validation and apply uncertainty and sensitivity analysis? In addition to highlighting existing challenges, we also point out directions for further research.

2 Overview of indicators and indices

In general, indicators consist of various pieces of data capable of synthesizing the characteristics of a system. When these indicators are aggregated they are called index or composite indicator (Saisana and Tarantola, 2002). Overall, the construction of an index comprehends 7 steps (Fig. 1). First, the phenomenon to be measured is defined, so that the index results can provide a clear understanding of this phenomenon (Nardo et al., 2008). Then, the indicators used to measure the phenomenon are selected. This should be done carefully as the results reflect the quality of the selected indicators.

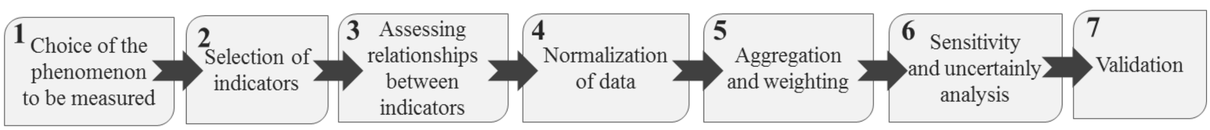

Fig. 1 Overview of the different steps involved in constructing an index.

In the third step, the relationships between the selected indicators are identified. Indicators with similar characteristics can be grouped aiming to reduce the number of variables. To this end, statistical analysis (e.g. principal component analysis - PCA) or expert knowledge can be used to decide whether the indicators are sufficient or appropriate to describe the phenomenon (Nardo et al., 2008). After selecting the indicators, they need to be normalized to a common scale before being aggregated into an index as they usually have different units of measurement (see Table 1 for the main normalization methods). By doing so, problems with outliers can also be reduced (Jacobs et al., 2004).

Table 1 Characteristics of the main normalization methods used for building indices.

Method	Equation	Description	Reference

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Ranking	$y_{in} = \mathrm{Rank}(x_{in})$	Based on ordinal variables that can be turned into quantitative variables.	Carlier et al. (2018)
Z-scores	$y_{in} = \frac{x_{in} - \bar{x}_{in}}{\sigma_{\bar{x}_{in}}}$	Converts all indicators to a common scale with a mean of zero and a standard deviation of one.	Gerrard (2018)
Min-Max	$y_{in} = \frac{x_{in} - \min(x_{in})}{\max(x_{in}) - \min(x_{in})}$	Rescales values between 0 (worst rank) and 1 (best rank). It subtracts the minimum value and divides it by the range of the maximum value subtracted by the minimum value.	Jha and Gundimeda (2019)
Distance from the group leader	$y_{in} = \frac{x_{in}}{\max(x_{in})}$	Rescales values between 0 and 1. It is defined as the ratio of the value of the indicator to its maximum value.	Munyai et al. (2019)
Division by total	$y_{in} = \frac{x_{in}}{\sum(x_{in})}$	It is defined as the ratio of the value of the indicator to the total value for the indicator	Jamshed et al. (2019)
Categorical scale	$y_{in} = \begin{cases} 0 \text{ if } x_{in} < P^{15} \\ 20 \text{ if } P^{15} \leq x_{in} < P^{25} \\ 40 \text{ if } P^{25} \leq x_{in} < P^{65} \\ 60 \text{ if } P^{65} \leq x_{in} < P^{85} \\ 80 \text{ if } P^{85} \leq x_{in} < P^{95} \\ 100 \text{ if } x_{in} \leq x_{qc}^{t} \end{cases}$	Assign a value for each numeric or qualitative indicator. Values are based on percentage.	Andrade and Szlafsztein (2018)
Binary standard	None	It is calculated using simple Boolean 0 and 1 (false and true) values.	Garbutt et al. (2015)

Note: y is the transformed variable of x for indicator i for unit n. $P^i$is the i-th percentile of the distribution of the indicator x_{in}, and pan arbitrary threshold around the mean.

The fifth step comprises the weighting and aggregation of the indicators. Weights can be assigned to indicators to demonstrate their importance in relation to the studied phenomenon (see Table 2 for the main weighting methods). Given that it may be difficult to find an acceptable weighting scheme, equal weights are often used, which implies that all criteria are "worth" the same (de Brito et al., 2018). Alternatively, an equal weighting scheme could be a result of a lack of knowledge about the indicators' importance. After the indicators are weighted, they are aggregated. The most common aggregation methods are linear and geometric. The linear method consists of the weighted and normalized sum of indicators whereas the geometric aggregation represents the output of the indicators whose exponent is their assigned weight (Nardo et al., 2008).

Table 2 Characteristics of the main weighting methods used for building indices.

Type	Method	Description	Reference
-	Equal weighting	All indicators receive the same weight.	Hernández-Uribe et al. (2017)
Statistically-based	Principal component analysis (PCA) / Factor Analysis	PCA is used for factor extraction. The weights are obtained from the rotated factor matrix since the area of each factor represents the proportion of the total unit of the variance of the indicators that is explained by the factor.	Gu et al.(2018)
	Entropy method	Weights are assigned based on the degree of variation of the indicator values.	Lianxiao and Morimoto (2019)
Participatory or expert-based	Expert opinion	Experts agree on the contribution of each indicator for the studied problem.	Shah et al. (2018)
	Public opinion	They focus on the notion of people's concern about certain problems measured by the indicators.	Schuster-Wallace et al. (2018)
	Multi-criteria decision-making (MCDM)	It is a set of methods based on multiple criteria and objectives for structuring and evaluating alternatives.	de Brito et al. (2018)

The sixth step consists of sensitivity and uncertainty analyses (see Table 3 for the main uncertainty and sensitivity methods). The first evaluates the contribution of the uncertainty source of each indicator to the variance of the results, while the latter focuses on how the uncertainty of each indicator propagates through the index structure and affects the outputs (Saisana et al., 2005; Saisana and Tarantola, 2002).

The final step comprises the validation of the index results. This is crucial to verify if they are consistent with the real system and have a satisfactory precision range. Validation can be achieved by using independent secondary data that refer to observable outcomes. Since vulnerability is not a directly observable phenomenon, its validation requires the use of proxies such as mortality and build environment damage (Schneiderbauer and Ehrlich, 2006), post event-surveys (Fekete, 2009), number of disasters (Debortoli et al., 2017) and emergency service requests (Kontokosta and Malik, 2018).

Table 3. Characteristics of the main methods for uncertainty and sensitivity analysis used for building indices.

Method	Description	Reference
One-at-a-time sensitivity analysis	By changing input data parameters, it was verified how these disturbances affected the results when all the other parameters remained constant.	de Brito et al. (2019)
Monte Carlo simulation	Computational algorithm which uses a probabilistic method that uses repeated random sampling	Feizizadeh and Kienberger (2017)
Statistical tools	Use of statistical tools such as regression, correlation analysis and cross-validation	Moreira et al. (2021), Nazeer and Bork (2019)

3 Methods

A bibliographic search was performed by focusing on studies that constructed flood vulnerability indexes. The Web of Science (WoS) database was searched using the following keywords to identify peer-reviewed articles published since 1945: ((“flood” OR “flooding”) AND (“index” OR “composite indicator”) AND “vulnerability” NOT “coast*”). Only the abstract, title, and keywords were searched. This narrowed the search space substantially and enabled us to exclude irrelevant articles.

These queries elicited over 348 articles published between 2002 and 2019. At first, the title, abstract, and keywords were screened manually to exclude irrelevant references. After this preselection, the full text of 84 selected papers was revised in detail. An additional of 11 articles were included as they were mentioned in the selected articles but are not included in the WoS database.

Following their selection, the articles were classified according to: (1) publication year; (2) study area country; (3) spatial scale (e.g. neighborhood, household, city); (4) region classification (e.g. urban, rural or both); (5) number of indicators; (6) whether or not there was a reduction of the indicators (e.g. PCA or expert knowledge); (7) temporal dynamics (pre or post-flood); (8) normalization, aggregation, and weighting methods used; and (9) if there uncertainty and validation analysis were performed. A complete list of the reviewed papers is presented in the Supplementary Material Table S1.

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4 Results and Discussion

4.1 Flood vulnerability indices at a glance

An increasing number of studies that built flood vulnerability indices can be observed in recent years, with about 80% (n=76) of the articles being published since 2015 (Fig. 2a) - the year the Sendai Framework for Disaster Risk Reduction (UNISDR, 2016) was created. This is not surprising given the strong call for vulnerability assessment in the Sendai Framework. Therefore, the growing number of publications may result from the increasing awareness of flood-disasters prevention and reduction policies as well as the easiness of using indices to address complex and multidimensional issues such as flood vulnerability. Alternatively, this increase may just match a general rise in published papers. To investigate this, we calculated the increase of flood vulnerability studies in relative terms based on a normalization according to the number of all flood publications in the WoS database. Results show that the increase in research on flood vulnerability indices is significantly greater than the increase of published flood articles (Appendix A Fig. A1).

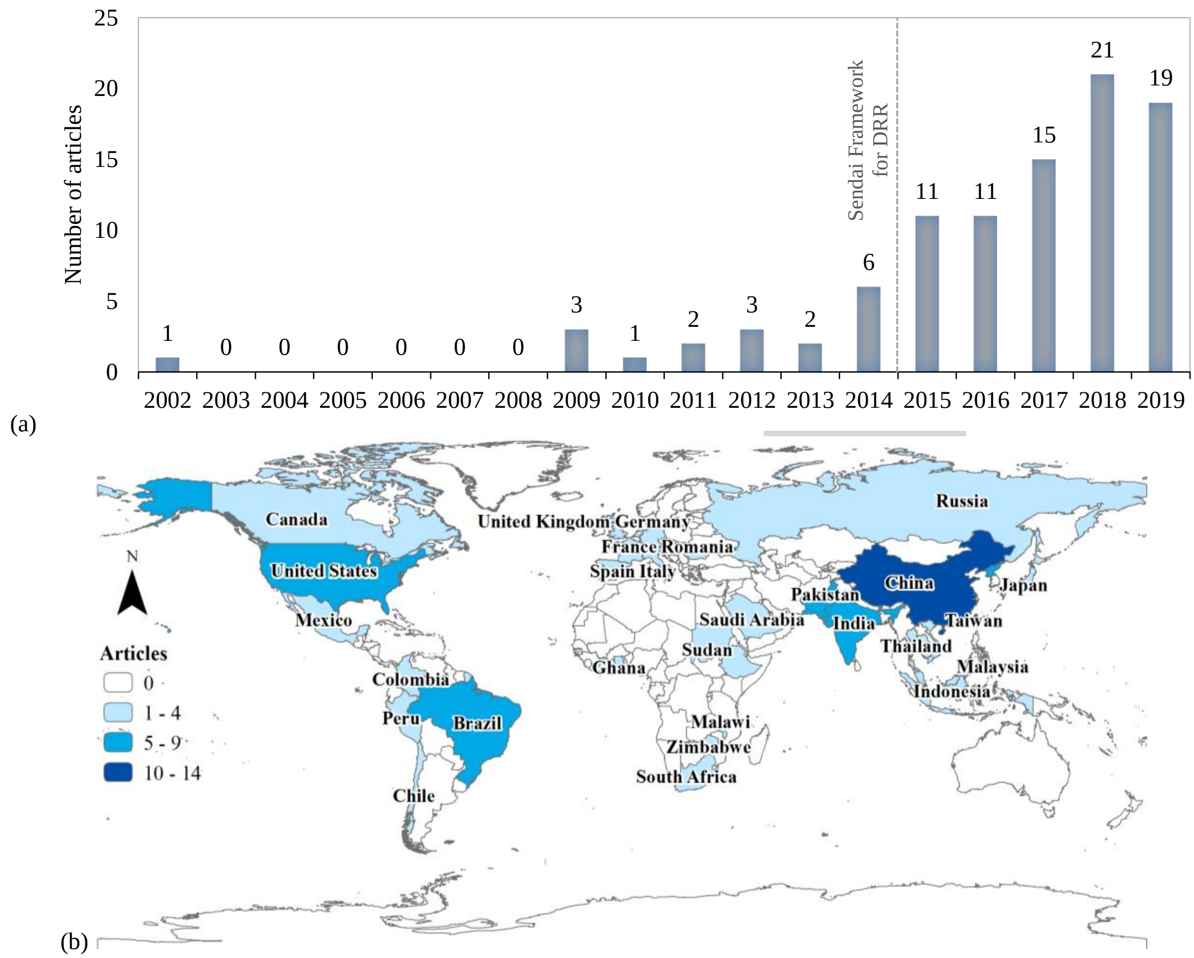

Fig. 2. Flood vulnerability index studies: (a) Temporal distribution from 2002 to 2019; and (b) Geographical distribution.

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Overall, most of the assessments were conducted in Asia (45.3%), followed by America (24.2%), encompassing 38 countries in total (Fig. 2b). This was expected as, according to the EM-DAT statistics, between 2002 and 2019 Asia showed the highest amount of deaths caused by floods (1027 deaths) (CRED, 2019). As such, the studies are highly concentrated in a few countries, namely China (n=14), Brazil (n=8), India (n=6), Pakistan (n=6), and United States (n=6). Meanwhile, there were fewer studies in East and West Africa despite the frequent occurrence of floods and the high mortality they cause across these regions.

In terms of spatial scale, most of the studies were conducted at the neighborhood scale (62.1%), followed by city (14.7%), household (12.6%), group of cities (7.4%), various scales (2.1%), and federal state (1.1%). Similar outcomes were obtained by Diaz-Sarachaga and Jato-Espino (2020), which found out that vulnerability studies at national and regional scales are infrequent. The neighborhood scale was the dominant scale in all continents (Fig. 3) as it is the smallest unit where data is available for large areas, generally through census data. Only 8 studies (8.4%) were conducted at the basin level (i.e. group of cities) and few articles (n=2) conducted assessments across various scales. For instance, Balica et al. (2009) evaluated the vulnerability at the basin, sub-basin, and city scales. Similarly, Remo et al. (2016) compared three scales (i.e. census blocks, communities, and counties) and found out that the results generally mirrored each other. None of the considered articles draw conclusions at the national or global level.

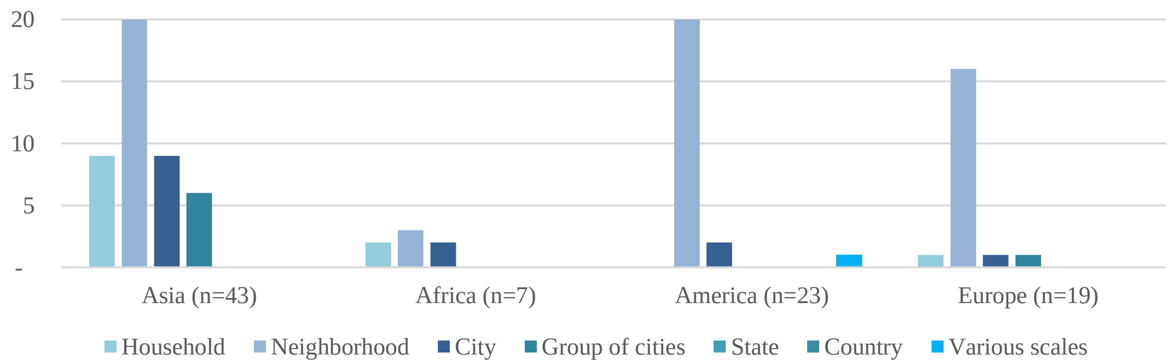

Fig. 3. Classification of papers of flood vulnerability in terms of scale in continents.

Around 40.0% of the studies were applied to urban areas, 15.8% to rural areas and 44.2% to both. The high prevalence of studies that consider both urban and rural areas is related to the data availability, as the census tracks usually encompass the entire perimeter of a municipality. At the neighborhood scale, most studies considered only urban areas (53.4%) (Fig. 4). Conversely, studies at the household scale were developed mainly in in rural areas (58.3%). This can be explained by the lack of data in rural areas. Therefore, in these cases, it is necessary to collect data via household surveys.

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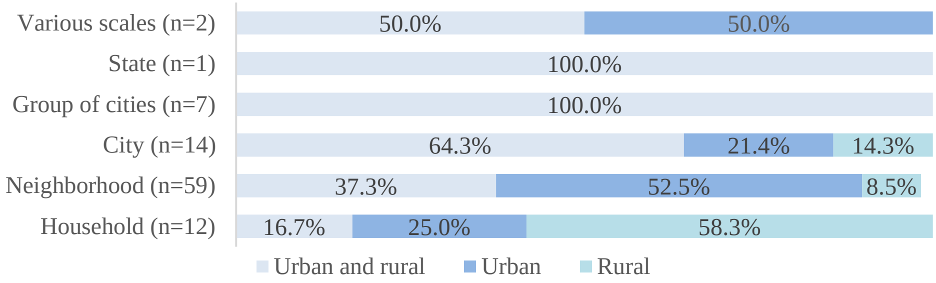

Fig. 4. Classification of studies in terms of rural and urban areas and spatial scale.

4.2 Indicators used to characterize flood vulnerability

Table 4 shows the most frequent indicators grouped into social, economic, physical and, coping capacity dimensions. In summary, social and economic indicators such as population density (37.9%), illiteracy rate (32.6%), unemployment rate (29.5%), female rate (28.4%), per capita income (25.3%), and elderly rate (22.1%) were the most commonly-used vulnerability indicators (Table. 4). This is similar to the results obtained by Rufat et al. (2015), who found out that poverty and deprivation, per capita income, unemployment rate, elderly and children were the most common indicators of social vulnerability. Nevertheless, widely used indicators found by the authors were not identified or were rarely used in our sample. These include, for example, stress and mental health, hygiene and sanitation, social networks, and experience with floods (Schneiderbauer and Ehrlich (2006).

Table. 4. Most commonly-used flood vulnerability indicators. Only indicators used in at least 4 articles are shown here.

Dimension	Indicator	N of articles
Social	Population density	36 (37.9%)
	Illiteracy rate	31 (32.6%)
	Unemployment rate	28 (29.5%)
	Female rate	27 (28.4%)
	Elderly rate	27 (28.4%)
	Education level	23 (24.2%)
	Male rate	11 (11.6%)
	Children rate	11 (11.6%)
	Inhabitants aged 0-15	11 (11.6%)
	Population growth	10 (10.5%)
	Total population	9 (9.5%)
	Persons with disabilities	7 (7.4%)
	Family members	7 (7.4%)
	Single parents with young children	6 (6.3%)
	Household headed by females	6 (6.3%)
	Cultural heritage	5 (5.3%)
	Household member with illness	5 (5.3%)
	Children mortality	5 (5.3%)
Economic	Per capita income	24 (25.3%)
	Gross domestic product (GDP) per capita	11 (11.6%)
	Population poor	10 (10.5%)

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	Rented houses	10 (10.5%)
	Household income	9 (9.5%)
	Dependency rates	9 (9.5%)
	Own vehicle	8 (8.4%)
	Percent of homeownership	5 (5.3%)
Physical	Household without sanitation	19 (20.0%)
	Household without safe water	14 (14.7%)
	Building material	14 (14.7%)
	Road network	12 (12.6%)
	Physical conditions of the building	11 (11.6%)
	Building location	9 (9.5%)
	Population in flood area	9 (9.5%)
	Urban area	8 (8.4%)
	Household without electricity	8 (8.4%)
	Number of floors	6 (6.3%)
	Building age	5 (5.3%)
	Building type	5 (5.3%)
	Number of hospitals	5 (5.3%)
Coping capacity	Early warning system	11 (11.6%)
	Past flood experience	7 (7.4%)
	Emergency committee	5 (5.3%)
	Flood insurance	5 (5.3%)

The studies used a median of 16 indicators. Although 32.6% (n=31) of the studies used more than 20 indicators (e.g. Sam et al., 2017), most of them (58.0%) did not apply any method for reducing the number of variables. Among the studies which conducted reduction, the mostly-used technique was the PCA, which was applied to 35.5% (n=11) of the indices that used more than 20 indicators (e.g. Aroca-Jimenez et al., 2017; Grosso et al., 2015; Török, 2018). In addition to PCA, some studies used other approaches, for example, based on expert opinion (e.g. de Brito et al., 2018) or based on indicators with a high Pearson correlation (e.g. Kotzee and Reyers, 2016).

4.3 Temporal dynamics

In order to identify if the articles included the temporal dynamics of vulnerability, the indices were classified into: pre-event (before), event (during) and post-event (after) Kobiyama et al. (2006). Most of the studies focused on assessing past vulnerability trends (88.4%) and only 12.6% explored post-event flood vulnerability (e.g. (Carlier et al., 2018; Miguez and Veról, 2017). None focused on the vulnerability during the event or elaborated projections for future vulnerabilities.

The indicators used differed according to the temporal scale considered. Post-event indices encompassed human, economic and material damages to quantify the flood vulnerability (Table 5). Variables such as mitigation, damages and coping behavior after experiencing a flood were often considered (Abbas et al., 2018). For instance, Rogelis et al. (2016) compared the results of the most vulnerable areas by ranking the basins according to the observed impacts from highest to lowest damage in terms of: number of fatalities, injured people, evacuated people, and number of affected houses.

Table 5. Indicators used for flood vulnerability assessment through post-event approach.

Damage Type	Indicator	Reference(s)
Human	Human deaths	Chaliha et al. (2012); Baeck et al. (2014); Abbas et al., (2018)
	Injured family members or human losses	Abbas et al. (2018); Ahmad and Afzal (2019)
	People suffering from poor health conditions due to floods	Chaliha et al. (2012), Jamshed et al. (2019)
	Population affected	Chaliha et al. (2012)
	Displacement	Okazawa et al. (2011)
	Domestic violence after a flood	Abbas et al. (2018)
	Left house due to flood	Abbas et al. (2018)
	Vulnerability to the dissemination of water borne diseases	Abbas et al. (2018); Miguez and Veról (2017)
	Access to safe water after a flood	Jamshed et al. (2019)
	Access to sanitation after a flood	Jamshed et al. (2019)
	Degradation of water quality	Jamshed et al. (2019)
Econo-mic	Affected villages	Chaliha et al. (2012), Jamshed et al. (2019)
	Crop lost value	Chaliha et al. (2012)
	Economic loss regarding animal husbandry	Ahmad and Afzal (2019)
	House damage value	Chaliha et al. (2012)
	Borrowed money	Abbas et al. (2018)
	Decrease in food expenditure	Abbas et al. (2018)
	Increase in medical cost	Abbas et al. (2018)
Material	Area affected by flood	Chaliha et al. (2012); Carlier et al. (2018); Okazawa et al. (2011)
	Building damage	Chaliha et al. (2012); Carlier et al. (2018); Bertilsson et al. (2019), Jamshed et al. (2019)
	Damages to public utilities	Chaliha et al. (2012)
	Number of killed livestock's	Chaliha et al. (2012)
	Crop damage	Abbas et al. (2018), Jamshed et al. (2019)
	Damage to house, livestock and, assets	Abbas et al. (2018), Jamshed et al. (2019)
	Schools damaged by flood	Jamshed et al. (2019)

4.4 Indicator normalization, weighting and aggregation

Concerning the indicators normalization, the most used approach was Min-Max (30.5%), followed by Z-score (12.6%) and Distance from the group leader (12.6%) (Table 6a). Five studies applied other methods. For example, Aroca-Jimenez et al. (2017; 2018) expressed the indicators' values in percentage or per capita value, and de Brito et al. (2018) used fuzzy functions to normalize the indicators. It is important to note that most papers did not specify the normalization method used (11.6%), which limits the index reliability.

Among the weighing approach types, statistical methods were the most applied (30.5%), especially the PCA method (21.1%). The high use of PCA can be attributed to the pioneering work by Cutter et al. (2003), which recommended the use of a factor analytic approach. Other less common statistical methods include dividing the indicator values by the total or maximum value (e.g. (Okazawa et al., 2011), hot spot analysis (e.g. (Kubal et al., 2009) and the unequal weighting method (e.g. (Kablan et al., 2017).

Many authors recommend the use of participatory methods for weighing the indicators such as the use of multicriteria decision-making (MCDM) tools. It is assumed that, if practitioners and experts are involved in creating an index that they find useful,

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it is more likely they will trust its results (Oulahen et al., 2015). In the present study, AHP was the most common MCDM technique, which corroborates the results by de Brito and Evers (2016). These authors attributed this preference to the fact that AHP is a straightforward and flexible method. This method was applied separately in 10 papers and together with other methods in 5 papers, totaling 16.0% of the reviewed articles. Among the less common MCDM methods, Promethee (Daksiya et al., 2017) and ANP (de Brito et al., 2018) techniques are worth mentioning.

Table 6 (a) Normalization methods; and (b) weighting methods.

a

Normalization Method	N	%
Min-Max	29	30.5
Z-score	12	12.6
Distance from the group leader	12	12.6
Unspecified	11	11.6
None (All indicators had the same unit)	11	11.6
Ranking	7	7.4
Categorical scale	3	3.2
Binary standard	3	3.2
Division by total	2	2.1
Others	5	5.3
	95	100

b

Type	Weighting Method	N	%
Statistically-based methods	PCA – weighting by factor scores	17	17.9
	PCA – equal weighting	3	3.2
	Entropy method	1	1.1
	Other statistical methods	8	8.5
Participatory or expert-based methods	Analytical Hierarchy Process	10	10.5
	Public opinion	6	6.3
	Expert opinion	2	2.1
	Other MCDM techniques	3	4.2
Others	Equal weighting	23	24.2
	Other methods	7	7.4
	Defined by the authors	8	8.4
	Unspecified	6	6.3
		95	100

A total of 7 articles used other weighting methods, including the entropy method (Lianxiao and Morimoto, 2019), Delphi technique (Yang et al., 2018b); and expert scoring (Wu et al., 2015). Furthermore, about one-fourth (24.2%) of the papers attributed equal weights and 6.3% did not specify the weighting method used (Table 6b). Some authors preferred not to weight indicators because they assumed that these indicators are equally important for vulnerability calculation (Yoon, 2012), whereas others pointed out that there is insufficient evidence to attribute importance to one factor over another (Fekete, 2011).

In terms of aggregation, the majority of the articles (80.0%) used linear aggregation, followed by geometric aggregation (10.5%) and mixed methods (4.2%). The linear method is useful when all indicators have the same unit or after they are normalized. The geometric aggregation is preferred when the interest is to assess the degree of non-compensation between the indicators. In linear aggregation, compensation is constant, while in geometric aggregation the compensation is lower for indices with low values (Nardo et al., 2008). Nevertheless, the geometric method has a limitation when indicators with very low scores are compensated by indicators with high scores (Gan et al., 2017).

It is important to mention other aggregation methods used (5.3%). For instance, Abebe et al. (2018) used the Bayesian Belief Network (BBN), which is formed by a graphical network representing the cause-effect relationships between the different indicators (Pearl, 1988). Yang et al. (2018a) applied the Shannon entropy method. In a similar study, Yang et al. (2018b) used the Shannon entropy method to calculate the indicators´ inhomogeneity. More recently, Amadio et al. (2019) used a non-compensatory aggregation method to compensate the low performance of one indicator by some higher performance of another indicator. Finally, Chiu et al. (2014) used the Fuzzy Comprehensive Evaluation Method (FCEM) to aggregate the indicators.

4.5 Uncertainty, sensitivity and validation

Each step of the construction of flood vulnerability indices carries uncertainty (Saisana et al., 2005)., which is added to the ones associated with the randomness of flood events (Merz et al., 2008). Therefore, to ensure a better index quality and verify the results' robustness, uncertainty analysis should be conducted. Despite its importance, only 3 (3.2%) of the reviewed papers performed uncertainty analysis: Nazeer and Bork (2019) observed variations in the final results changing input variables; Feizizadeh and Kienberger (2017) and Guo et al. (2014) applied Monte Carlo simulation and set pair analysis, respectively.
With respect to sensitivity analysis (SA), only 9 papers (9.5%) performed it. Most articles applied local SA by comparing the results obtained by changing input methods, such as choosing different weights (Müller et al., 2011; Nazeer and Bork, 2019; Rogelis et al., 2016), aggregation methods (Fernandez et al., 2016; Nazeer and Bork, 2019) or indicators (Rogelis et al., 2016; Zhang and You, 2014). In turn, Abebe et al. (2018) quantified sensitivity through variance reduction and mutual information. de Brito et al. (2019) performed spatial SA by computing the vulnerability class switches when the indicator weights were changed. Only Feizizadeh and Kienberger (2017) performed the global sensitivity analysis (GSA).
Although the number of flood vulnerability studies has increased, few studies attempted to validate the obtained outcomes (Fekete, 2009). Of the reviewed articles, only 11 (11.6%) validated the results, mostly using maps with flooded areas (n=7), flood damage (n=3), and expert's opinion (n=1).

5 Persisting gaps and future research

Despite the increasing number of research on flood vulnerability indices since 2015, a series of persistent knowledge gaps of methodological nature were found in our systematic review. Here, we summarize these gaps and provide a research agenda with needs that should be addressed in future research.
The first challenge refers to the spatial scale as vulnerability is not only site-specific but also scale-dependent (Ciurean et al., 2013). The choice of the spatial scale in the reviewed articles was mostly driven by data availability and hence most of them were applied at the neighborhood level using census tracks. There were no studies at the national level and only 8 papers (8.4%) constructed vulnerability indices using data at the basin scale. Nevertheless, these scales are often used for flood risk management and are necessary to enable the comparability of regions and to define hot-spot areas where intervention is needed (Balica et al., 2009; Fekete et al., 2010). Conversely, studies at the household level were also rare in our sample (n=12). Yet,

aspects related to the citizens' coping capacities can only be captured at this spatial scale. An additional issue is the problem of down- or up-scaling that implies different levels of generalization. Hence, multi-level and cross-scale studies are needed. They allow for a better understanding of scale implications, including their benefits and drawbacks. A better understanding of the linkages between urban-rural linkages is also needed instead of studying it in isolation. To this end, the framework proposed by Jamshed et al. (2020) could be used.

A second gap is that indicators related to the populations' coping and adaptive capacity were rarely used. A focus was given to social indicators that increase people´s vulnerability. Similar to the scale issue, this preference is driven due to data availability issues as social indicators (e.g. age, gender) are easily accessible. Nevertheless, the capacity of people to anticipate, cope with, resist and recover from disasters is equally important to understand the risk. In fact, even poor and vulnerable people have capacities (Wisner et al., 2012). Therefore, when dealing with flood vulnerability, other relevant indicators such as risk perception (Carlier et al., 2018), past flood experience (Beringer and Kaewsuk, 2018). These indicators require local research, which demands time and financial resources. Indeed, information on citizens' adaptive behavior and perception requires longitudinal or quasi-experimental studies that allow to capturing behavioral dynamics over time (Kuhlicke et al., 2020). As an alternative, people's risk perception could be derived from widely available data sources, including, for instance, Google trends (e.g. Kam et al, (2019) and twitter statistics (Dyer and Kolic, 2020).

Still with regard to the indicators used, many of the studies used variables that overlap with each other. In this context, some indices used more than 20 indicators to measure flood vulnerability and did not apply any technique (e.g. PCA, expert-based) to reduce this number. This can decrease the explanatory power of the index. A further issue is that the reasoning for variable selection was often not given or it was justified based on previous studies, without taking into consideration the study area specificities or conceptual frameworks. Due to the difficulty and time involved in developing indicators, low-quality databases are normally used (Freudenberg, 2003). For adequate indicators' selection, the analytical soundness, measurability, relevance to the phenomenon being measured and the relationship to each other (e.g. interrelationships and feedback loops) should be taken into account. Furthermore, more theoretically grounded research is needed to generate robust evidence for selecting the input indicators.

All of the vulnerability indices reviewed here are static and represent a snapshot of vulnerability. Hence, they do not capture the complexities and temporal dynamics of vulnerability. Few studies focused on measuring flood vulnerability pos-event. Nevertheless, the drivers of vulnerability can vary considerably over time. Results by Kuhlicke et al. (2011) and Reiter et al. (2018) show that the exposed citizens (e.g. elderly and children) may be less vulnerable during the preparatory phase of a flood but highly vulnerable during the recovery phase. Hence, incorporating the phase of the flood disaster is key to improving the validity of vulnerability indices (Rufat et al., 2015). To account for temporal context, the indicator can be differentiated according to different phases of a flood disaster: preparedness, response and recovery phases. Such a phase-oriented approach could inform variable selection and weighting. In addition to this, there is a need for research looking into future vulnerabilities as preventive planning for FRR requires a forward-looking perspective (Birkmann et al., 2013; Garschagen and Kraas, 2010).

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These could make use of, for instance, population growth projections or by employing qualitative futuring techniques (Hoffman et al., 2021).

Similar to the selection of the indicators, several articles did not indicate why a specific normalization and weighting technique was chosen. Additionality, some did not explicitly specify any normalization (11.6%) or weighting (6.3%) method. Nevertheless, the use of arbitrary techniques without testing different methods and their assumptions, increases the subjective judgement error. Hence, it is imperative for further studies to be more rigorous and present the reasoning behind such choices. Furthermore, there was an over-reliance on the use of the AHP weighting method and studies comparing different normalization and weighting techniques were rare (7.4%). Future research should tackle this by exploring different alternatives for evaluating indicator weights (e.g. expert-based, MCDM, statistical approaches) and compare the findings by means of validation and sensitivity analyses.

A final persisting gap is that few vulnerability indices conducted any sort of validation, sensitivity and uncertainty analysis. Less than 14% of the studies have conducted any form of validation of their results using impact data (e.g. Rezende et al. (2019) and only 9.5% have conducted a statistical sensitivity or uncertainty analysis. The lack of these analyzes results in vulnerability outputs incoherent with the local reality, being able to over or underestimate the vulnerability spatially, which difficult decision-makers to reduce flood vulnerability. Fekete (2009) points out several difficulties in this process, such as the difficulty of finding empirical evidence about vulnerability; the vulnerability concept is holistic and generic with complex relationships, as well as being multidimensional; and vulnerability is difficult to estimate for methodological reasons. Further research is needed on the validation of vulnerability outcomes (including technical and user validation) and analysis of the sensitivity of the contribution of individual indicators to the obtained results. These findings are in line with the gaps identified by Hagenlocher et al. (2019), de Brito and Evers (2016) and Moreira et al. (2021).

6 Conclusions

The present study reviewed 95 articles from 38 countries that constructed flood vulnerability indices. In summary, despite the increasing number of studies and advances made, the review has revealed and re-confirmed a number of persistent knowledge gaps. Only 11.6% of studies focused on indicators that address post-event conditions related to flood damage and consequences and none of them investigated future vulnerabilities. Coping and adaptive capacity aspects were frequently ignored. Most did not apply sensitivity (90.5%) and uncertainty analyses (96.8%) nor performed results validation (86.3%). This demonstrates a limitation of the reliability of these indices. It is clear from the literature that the challenge for further research is to foster the development of dynamic vulnerability assessments that consider citizens´ coping capacities and take the uncertainty involved in all steps of the index building process into account, including the selection of indicators, normalization, weighting, and aggregation. This is required in order to advance our understanding of flood vulnerability and support pathways towards flood risk reduction.

Appendices

APPENDIX A

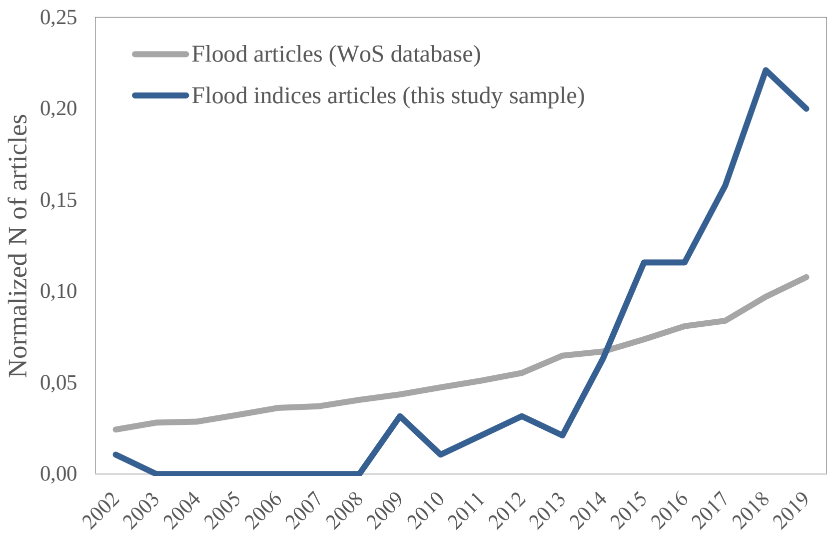

Fig. A1 Normalized number of flood vulnerability indices and flood articles according to the Web of Science database. For the Flood articles search, the keyword "flood*" was used.

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Competing interests. The authors declare that they have no conflict of interest.

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