

## Systematic Review

# Quantifying Community and Infrastructure Vulnerability to Floods: Implications for Land-Use Planning and Resilience

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## Abstract

Flood-vulnerability assessment uses diverse and often incompatible methods, limiting comparison across community, regional, and infrastructure scales and constraining land-use and resilience planning. This systematic review, conducted and reported in accordance with PRISMA 2020, examined quantitative flood-vulnerability methods published from 2000 through 2025, a period spanning the emergence and maturation of contemporary quantification approaches. Scopus was searched on 23 January 2026 and updated on 28 May 2026. Eligible studies were English-language, peer-reviewed articles applying a reproducible procedure to quantify flood-related vulnerability, susceptibility, fragility, damage, loss, disruption, or coping or adaptive capacity; hazard-only and purely conceptual studies were excluded. Of 371 screened records, 144 were included. Data were extracted manually, with reviewer verification, against a standardized coding framework capturing application scale, method family, construct, data source, weighting, validation, uncertainty treatment, and planning relevance, yielding 217 harmonized indicators across 226 indicator–component assignments; where source studies left components undefined, indicators were assigned by structural position within the study’s own model, and otherwise by reviewer consensus. Community-scale studies relied mainly on composite socioeconomic indices; regional-scale studies combined geospatial data with multicriteria decision analysis; infrastructure-scale studies used fragility, probabilistic, hydraulic, and network-performance models, exemplified by Monte Carlo–derived fragility curves and Manning-based hydraulic models. Inconsistent construct definitions, limited validation, weak treatment of indicator interactions, and low transferability, the last arising from locally calibrated weights, census-bounded indicator availability, and damage models encoding local construction typologies, constrained comparison. Principal limitations are reliance on one database, restriction to English-language literature, and the absence of a common effect measure, unreported variance estimates, and methodological heterogeneity, which jointly precluded meta-analysis. For municipal managers and territorial planners, the consolidated inventory offers an immediately usable instrument: it allows existing local vulnerability metrics to be screened against a comprehensive reference set, component-level indicators measurable from current municipal GIS, census, and cadastral data to be selected, and those indicators to be embedded directly in floodplain overlay districts, zoning provisions, and stormwater requirements, provided they are locally calibrated before adoption.



Academic Editor: Jianming Cai

Received: 25 July 2026

Revised: 1 September 2026

Accepted: 6 September 2026

Published: 12 October 2026

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**Keywords:** flood vulnerability; land-use planning; vulnerability indicators; composite indices; machine learning; infrastructure resilience; systematic review; multi-criteria decision analysis; GIS-based assessment; floodplain management

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## 1. Introduction

Flooding is among the most frequent natural hazards, causing loss of life and substantial damage to property and infrastructure [1]. Drawing on the Emergency Events Database (EM-DAT), ref. [2] reports that 4845 flood disasters occurred worldwide between 1980 and 2020, causing average annual economic losses exceeding \$21 billion and approximately 5900 deaths per year [3]. These historical averages substantially understate present exposure and loss. Floods now account for between 35 and 40 per cent of weather-related disaster occurrences, and the number of recorded flood disasters has risen by 134 percent since 2000 relative to the two preceding decades, while the global population exposed to flooding increased from 28.1 million in 1970 to 35.1 million in 2020 [4].

Current global average annual losses from flooding are estimated at approximately US\$388 billion, and are projected to rise further under climate change: by 2050, average annual losses to infrastructure from riverine flooding are modelled to increase by between 5 per cent under a low-emission scenario (RCP 2.6) and 13 per cent under a high-emission scenario (RCP 8.5), reaching US\$407–439 billion annually, with markedly uneven regional trajectories that include projected increases exceeding 40 per cent in Western Asia, Melanesia, and Eastern Africa [4]. Therefore, comprehensive flood-risk assessment is essential for identifying potential human and economic consequences, strengthening the resilience of communities and infrastructure, and supporting risk-informed mitigation, preparedness, resource allocation, and emergency-management decisions [5–7].

As used in this article, risk-informed mitigation refers to measures taken in advance of a flood event to reduce its expected consequences, where the selection, siting, sequencing, and prioritization of those measures follow from quantified estimates of hazard, exposure, and vulnerability rather than from uniform design standards, historical precedent, or reaction to the most recent event. In the land-use context that concerns this review, it encompasses both structural measures, such as flood defenses, drainage capacity, retention structures, and the retrofitting of buildings and critical infrastructure, and non-structural measures, such as floodplain overlay districts, zoning and development controls, setback and freeboard requirements, stormwater and impervious-surface regulations, green-infrastructure provisions, and the targeting of resilience funding. It is distinguished here from preparedness, which concerns readiness for an event that is expected to occur; from response, which concerns action during and immediately after an event; and from adaptation, which concerns longer-term adjustment to changing climatic conditions. The distinction matters for the argument of this review, because it is specifically the mitigation stage at which quantified vulnerability estimates enter planning practice: mitigation undertaken without such estimates may still reduce harm, but it cannot allocate limited resources according to where harm is most likely to be concentrated.

In recent years, numerous studies have developed quantitative methods and analytical tools for assessing flood risk and vulnerability across different spatial and application scales [8–12]. These approaches can be broadly grouped into mathematical and index-based methods, machine-learning models, and software-supported assessment frameworks, as summarized in Table 1. Mathematical approaches use equations, composite indices, statistical relationships, or expert-derived weighting procedures to represent associations among flood-vulnerability indicators and assessment outcomes [10,13–15]. Machine-learning ap-

proaches use historical or simulated data to identify patterns and estimate relationships between relevant indicators and flood-vulnerability outcomes. Reviewed literature applies a broad range of algorithms rather than any single technique, and these serve distinguishable analytical purposes.

**Table 1.** Principal method families and analytical platforms used in quantitative flood-vulnerability assessment.

| Method Family                                           | Representative Approaches                                                                                         | Typical Output                                                                                              | Common Analytical Platforms                                                         |
|---------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------|
| Composite and index-based methods                       | Flood Vulnerability Index, Livelihood Vulnerability Index, Social Vulnerability Index, weighted composite indices | Standardized vulnerability score, vulnerability class, or comparative ranking                               | Microsoft Excel, R, Python, Stata, SAS, ArcGIS, QGIS                                |
| Multicriteria decision-analysis methods                 | AHP, fuzzy AHP, ANP, TOPSIS, VIKOR, entropy weighting, game-theory weighting                                      | Indicator weights, ranked alternatives, and spatial vulnerability maps                                      | ArcGIS, QGIS, Expert Choice, MATLAB, R, Python                                      |
| Statistical and probabilistic methods                   | Regression analysis, principal component analysis, Bayesian models, time-series analysis, Monte Carlo simulation  | Statistical relationships, vulnerability probabilities, component scores, and uncertainty estimates         | R, Python, SPSS, Stata, SAS, MATLAB                                                 |
| Machine-learning methods                                | Bayesian belief networks, artificial neural networks, decision trees, random forests, support-vector machines     | Predicted vulnerability class or probability, feature importance, and spatial prediction                    | Python, R, SAS, MATLAB                                                              |
| Hydrological and hydraulic modeling                     | Hydrological models, one- and two-dimensional hydraulic models, flood-inundation simulation                       | Flood depth, velocity, extent, and duration used as inputs to exposure, vulnerability, or damage assessment | HEC-RAS, SWMM, MIKE FLOOD, InfoWorks                                                |
| Fragility, reliability, and network-performance methods | Fragility curves, component-reliability models, probabilistic failure analysis, network-disruption models         | Failure probability, damage state, service disruption, and recovery performance                             | MATLAB, R, Python, specialized network-analysis software                            |
| Damage- and loss-assessment methods                     | Depth–damage functions, empirical damage models, replacement-cost models, scenario-based loss estimation          | Physical damage, economic loss, affected assets, and expected annual loss                                   | HAZUS, HEC-FDA, ANUFLOOD, FLEMO, MCM, JRC depth–damage functions, ArcGIS, R, Python |

Note: GIS and named software packages are treated as analytical platforms that support one or more quantification methods rather than as independent methodological families. They are listed here to indicate typical implementation environments; the platform used does not identify the method applied, since each platform supports methods from several families and each method family can be implemented on several platforms. Damage- and loss-estimation models are listed here in abbreviated form; Section 4.5.3 presents the complete inventory, with each model’s empirical or synthetic basis, country of development, principal intensity measure, and geographical scale of application.

Principal component analysis is used to reduce dimensionality among correlated indicators and to derive indicator weights from the structure of the data rather than from expert judgement [16,17]. Tree-based methods, including decision trees, random forests, and gradient-boosted decision trees, are used to classify vulnerability or susceptibility and to rank the relative importance of contributing indicators [18,19]. Support vector

machines and k-nearest-neighbour classifiers are applied to discriminate vulnerability classes where the boundary between them is not linearly separable, and artificial neural networks are used to model non-linear relationships between indicator sets and observed outcomes. Agglomerative hierarchical clustering and related unsupervised methods are used to group spatial units with similar vulnerability profiles without imposing pre-determined classes [20]. Bayesian belief networks occupy a distinct position within this family, representing indicators and outcomes as a directed graph of conditional dependencies and yielding posterior vulnerability probabilities rather than deterministic class assignments [21–23].

In this review, software packages are treated as analytical platforms that implement or support quantification methods rather than as independent methodological families. This distinction is substantive rather than merely organizational. A software package executes a procedure specified by the analyst; it does not determine the conceptual structure of that procedure, the indicators admitted to it, the weights assigned to them, or the criteria by which its outputs are validated. The relationship between platform and method is many-to-many: a geographic information system may implement a composite index, a multicriteria weighting scheme, a machine-learning classifier, or a damage function, while a single method such as the analytic hierarchy process may be implemented in a geographic information system, a spreadsheet, a statistical environment, or dedicated decision-support software. Platform identity therefore carries no information about the analytical approach adopted. Characterizing a study as “GIS-based” or by the name of a damage-estimation package, as is common in this literature, describes the execution environment while leaving unspecified the methodological choices that determine whether a vulnerability assessment is transparent, reproducible, and defensible. Throughout this review, studies are accordingly classified by method family, with the platform recorded separately as a distinct extraction field.

Flood vulnerability varies across events and locations because flood characteristics, exposed elements, socioeconomic conditions, infrastructure systems, environmental settings, data availability, and analytical choices differ. Consequently, studies use different constructs, indicators, weighting schemes, spatial resolutions, and validation strategies, producing results that are difficult to compare across contexts [18,24–26]. Figure 1 summarizes the principal sources and consequences of this methodological variability.

The figure is organized in three sequential layers. The first layer identifies sources of variability. Temporal variability arises because vulnerability is not a fixed property: the same population or asset may be differently vulnerable at the mitigation, preparedness, response, and recovery stages of a single event, and vulnerability profiles shift over years as demography, land cover, and infrastructure change. Spatial variability arises because the unit of analysis (household, neighborhood, municipality, watershed, or nation) determines which processes are visible and which are averaged away. Contextual variability arises from differences in climatic regime, flood mechanism, construction typology, institutional capacity, and the reporting systems that supply data. Methodological variability arises from the analyst’s own decisions. The first three sources are properties of the phenomenon and its setting; the fourth is a property of the assessment, and this distinction is central to the argument the figure makes.

The second layer traces how these sources propagate into the analytical decisions that together constitute a quantification procedure: how the assessed construct is defined and bounded, which indicators are admitted and which omitted, how heterogeneous indicators are normalized to a common scale, how they are weighted relative to one another, how weighted indicators are aggregated into component and composite scores, and whether and against what the resulting estimate is validated. Each decision is defensible in isolation, yet

each admits several defensible alternatives, and the alternatives are rarely reported as such. Variability entering at this layer is therefore compounded rather than merely transmitted: two analysts working from the same data on the same territory can arrive at materially different vulnerability estimates without either departing from accepted practice.

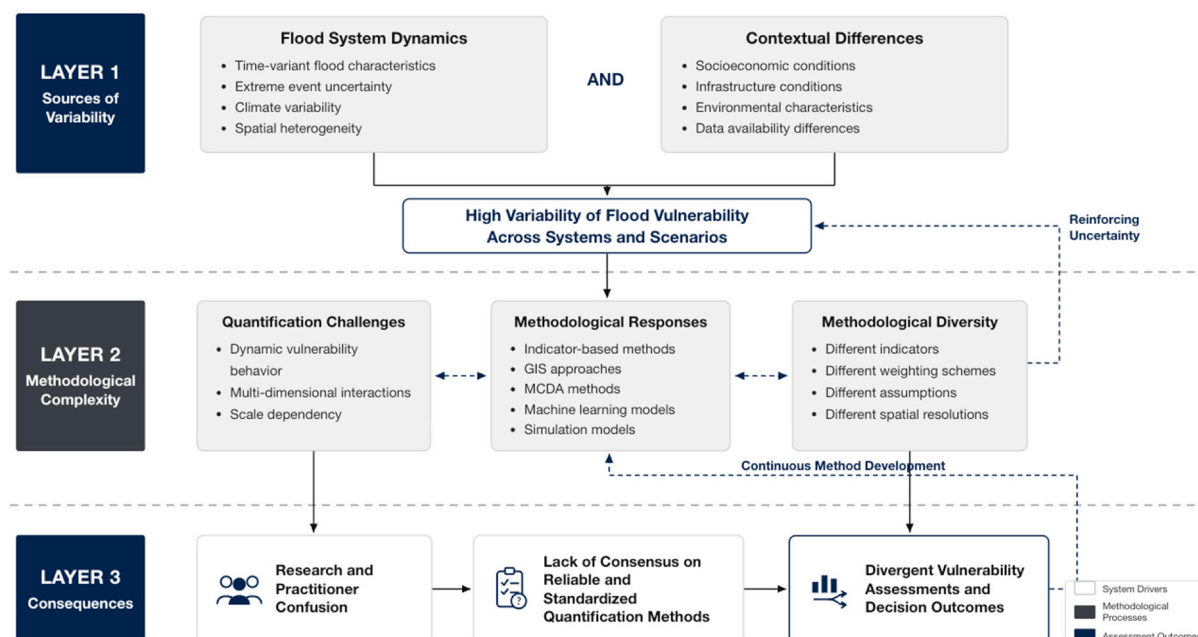


**Figure 1.** Sources and consequences of variability in flood-vulnerability assessment. Temporal, spatial, contextual, and methodological differences contribute to inconsistent quantification methods and decision outcomes.

The third layer identifies the consequences for research and practice. Vulnerability estimates become non-comparable across studies, since they are expressed on incommensurable scales and rest on differently defined constructs. Methods become difficult to transfer between contexts, because their weights and indicator sets are calibrated to the setting in which they were developed. Most consequentially for the purposes of this review, planning and investment decisions diverge: the same territory may be classified as high or low vulnerability depending on choices made at the second layer, with direct implications for zoning determinations, floodplain designations, and the allocation of resilience funding. The distinction drawn in the first layer matters here, because variability originating in analytical choice, unlike variability originating in the phenomenon itself, is remediable through transparent reporting, systematic comparison of methods, and standardization of the constructs and indicators on which they rest. Establishing that basis for comparison is the purpose of the present review.

The variability characterized in Figure 1 determines the form of enquiry appropriate to it. Where the object of study is the population of quantification methods itself, rather than an effect that those methods estimate, the analytical requirement is to establish what that population contains, how its members differ, and along which dimensions those differences fall. This requirement is met by a systematic review and is not met by the principal alternatives. A narrative review can describe methods but cannot establish that its coverage is complete, and completeness is not incidental here: the claim that the field is heterogeneous is only as strong as the assurance that heterogeneous cases were not selected preferentially. A bibliometric analysis can map the structure of the literature through citation and co-word relationships but does not reach the analytical content, the constructs, indicators, weights, and validation procedures, in which the variability resides.

A meta-analysis would be the appropriate systematic form if the studies reported a common effect measure with associated variance, and they do not, for the three reasons set out in Section 3.8. A primary comparative study, applying several methods to a single territory, would yield a controlled comparison but only for that territory, and would therefore reproduce in its own design the context-specificity that the review seeks to characterize.

Three features of the systematic form are decisive for this problem. First, a documented and reproducible search establishes the boundary of the evidence base, so that statements about the prevalence and distribution of methods rest on a defined population rather than on the reviewers' familiarity with it. Second, extracting identical fields from every included study under a common coding framework renders heterogeneity measurable rather than merely assertable, since differences between studies are visible only against a constant scheme of comparison; the standardized extraction form and the indicator harmonization procedure exist for this purpose, and the resulting inventory of 217 harmonized indicators is a direct product of it. Third, and with force in the present case, the systematic form makes the review's own analytical decisions auditable. A review whose central finding is that the field under-reports its construct definitions, weighting justifications, and validation procedures would be self-undermining were it not to report its own; the PRISMA-conformant documentation of search, screening, extraction, and appraisal is therefore a substantive requirement of the argument rather than a procedural formality.

Accordingly, this review pursues three objectives:

To catalogue systematically the indicators and quantification methods used to assess flood vulnerability for communities, regions, and infrastructure, establishing the range and relative prevalence of approaches in use (addressed in Sections 4.3–4.5, and in Appendix A);

To synthesize these methods into a unified knowledge framework that clarifies the relationships among vulnerability components, indicators, quantification methods, analytical platforms, and application scales (addressed in Section 4.2);

To identify methodological gaps and opportunities, particularly concerning indicator selection, indicator interaction, validation, and cross-method comparison, and to establish their implications for future research and for land-use planning practice (addressed in Section 5).

The remainder of the paper is organized as follows. Section 2 situates the review in relation to prior work and sets out the conceptual framing adopted for vulnerability components. Section 3 reports the review protocol, search strategy, eligibility criteria, extraction procedure, indicator harmonization, quality appraisal, and synthesis approach. Section 4 presents the distribution of included studies, the conceptual framework, the harmonized indicator inventory, and the quantification methods used at each application scale. Section 5 discusses indicator selection and interaction, methodological convergence and divergence, transferability, implications for practice, and limitations. Section 6 concludes.

## 2. Background

Several reviews have addressed parts of the flood-vulnerability literature, each valuable within its scope and each bounded by it. Ref. [1] reviewed flood-vulnerability assessment conducted through geographic information systems, organizing the field by spatial data type and mapping application, but treating the analytical platform as the unit of synthesis and therefore not addressing mathematical, statistical, or machine-learning approaches implemented elsewhere. Ref. [27] synthesized case studies of social vulnerability to floods and examined the empirical support for commonly used social indicators but confined the analysis to the social dimension and did not extend to physical, infrastructural, or ecological vulnerability.

Ref. [28] reviewed flood-risk management and the selection of mitigation measures, cataloguing damage-estimation software and management options, but framed the synthesis around risk management rather than the quantification of vulnerability itself. Ref. [29] proposed a model taxonomy for flood fragility and vulnerability assessment of buildings, providing a rigorous classification of empirical, analytical, and expert-based approaches at the structural scale, but by construction addressed buildings rather than communities, regions, or networked infrastructure systems.

Ref. [30] examined flood-vulnerability mapping approaches in developing countries and, in related work, the use of local and indigenous knowledge in indicator selection [31], with the geographical and epistemic scope deliberately bounded. Most recently, ref. [32] reviewed indicators, indices, and methodological approaches in research on social vulnerability to floods, identifying gaps in indicator justification and validation, again within the social dimension. Two of these reviews, refs. [30,32], met the eligibility criteria of the present review and are among the 13 review articles included in the corpus of 144; they are therefore discussed here both as prior syntheses and, in Section 4, as primary evidence. The remainder were consulted for background and citation chaining without being counted in the corpus.

Two patterns are evident across these reviews. First, each is organized around a single axis (one analytical platform, one vulnerability dimension, one exposed element, or one geographical context), with the consequence that no synthesis spans the community, regional, and infrastructure scales together. Second, and following from this, the indicator inventories they produce are not commensurable: indicators catalogued as social vulnerability measures in one review, as fragility parameters in another, and as risk-management inputs in a third are neither harmonized nor mapped to a common set of vulnerability components.

These reviews are individually valuable, and the present review draws on them for background and for citation chaining. Each, however, was constrained to a narrow methodological lens or a single application domain. Ref. [1] synthesized GIS-based assessment methods specifically, without addressing mathematical or machine-learning approaches. No existing review has systematically catalogued the full range of indicators used across these three application scales, nor synthesized how general quantification approaches (mathematical, machine-learning, and software-based) are operationalized within each. This represents a meaningful gap: practitioners and researchers currently lack a single reference that connects vulnerability theory (exposure, sensitivity, adaptive capacity) to the specific indicators and equations used to operationalize it across scales, which limits the ability to compare results or select appropriate methods for a given planning context.

Community-, regional-, and infrastructure-scale vulnerability are commonly examined in separate disciplinary literatures. Community-scale research generally draws on social-science and livelihood frameworks; infrastructure-scale research draws on structural, reliability, and network engineering; and regional-scale research draws on geospatial, hydrological, and planning methods. Flood impacts, however, cross these disciplinary and spatial boundaries. A flood may simultaneously damage housing, disrupt roads and utilities, and affect an entire watershed [33–36].

A flood that damages housing stock (community vulnerability) simultaneously degrades road and utility networks (infrastructure vulnerability) across a watershed [37–41], and the indicators used to measure each are frequently correlated or causally linked [42,43], such as population density influencing both social sensitivity and infrastructure load. This relationship operates through identifiable pathways rather than directly: higher settlement density is associated with greater impervious surface and reduced infiltration, increasing runoff volumes and surcharging drainage capacity [21,44–46], and with greater demand

on transport and utility networks during evacuation and recovery, where flood-induced disruption is correspondingly more consequential [39,42,47].

Recent evidence indicates that assessing these scales in isolation is not merely incomplete but produces identifiable methodological errors, in three respects. The first concerns magnitude. Assessments bounded by a single system cannot represent failure propagation between systems, and the resulting underestimation is substantial rather than marginal: ref. [40] reports that incorporating infrastructure failure cascades increases estimated storm- and flood-induced service disruption several-fold relative to assessments treating infrastructure systems independently, and comparable propagation effects across interconnected urban infrastructure are documented by [48] and, for a different hazard, by [49]. An assessment conducted at one scale therefore does not simply omit the others; it misstates the quantity it purports to measure.

The second concerns the treatment of cross-scale variables as fixed inputs. Community-scale assessments routinely incorporate accessibility, evacuation capacity, and distance or travel time to health facilities as indicators, and Appendix A records several such measures among the sensitivity indicators identified in this review. These quantities are not stable during a flood: ref. [39] documents extensive disruption of the transport network in the 2017 Mandra flood, and ref. [42] quantifies the degradation of travel times across the Houston freeway network during Hurricane Harvey. A community-scale assessment that treats pre-event accessibility as a fixed attribute therefore embeds an assumption that infrastructure-scale evidence contradicts.

The third concerns conceptual consistency. Because each literature assigns indicators to vulnerability components according to its own conventions, the same measured quantity may be coded differently depending on the tradition in which it is used. The present review provides direct evidence of this: of the 226 indicator–component assignments recorded in Appendix A, nine indicators received more than one component assignment because different source studies operationalized them in different conceptual roles, including road density, coded as physical exposure in one tradition and as social coping capacity in another. Single-scale synthesis conceals such divergences by construction, since it observes only one of the traditions in which an indicator is used.

The consequences of this incommensurability for practice are examined further in Section 5. By synthesizing indicators and methods across all three scales within one framework, this review enables researchers and planners to identify these cross-scale linkages and avoid the fragmented, single-scale assessments that have characterized prior flood vulnerability research [50,51].

Spatial resolution is not only a descriptive attribute of a study but a constraint on the methods available to it, and this partly explains why the method families identified in Section 4 align with application scale rather than being distributed evenly across it. Three restrictions operate. First, the unit of analysis fixes the number of observations: statistical and machine-learning methods requiring substantial samples, including principal component analysis, regression, and ensemble classifiers, are feasible where a territory yields hundreds of grid cells or census units, but not where it yields a few dozen administrative districts. Second, aggregation to a spatial unit destroys the within-unit variance on which asset-level methods depend; fragility functions and depth–damage curves relate a specific loading value to a specific structure, and a mean inundation depth across a district is not a quantity to which they can be applied. Third, indicator values, and therefore any weights derived from their covariance, are not invariant to the zonation on which they are computed, so weighting schemes calibrated at one resolution are not transferable to another even within the same territory. Method selection is therefore bounded by resolution before any consideration of conceptual suitability.

Beyond its contribution to flood vulnerability measurement, this review carries direct relevance for land-system science and land-use governance. Flood vulnerability indicators such as impervious surface area, building density, land cover composition, and floor area ratio are not neutral environmental variables; they are direct outputs of land-use decisions made by planners, zoning authorities, and floodplain managers [45,52,53]. The vulnerability quantification methods synthesized in this review therefore function as evidence bases for land-use policy: they identify which land-cover and land-development patterns measurably increase exposure and sensitivity to flooding, and which adaptive-capacity investments measurably reduce it.

These investments fall into three broad categories, which differ in their mechanism and in the instruments through which planning authorities can bring them about [54,55]. Nature-based solutions and green infrastructure reduce vulnerability by restoring or emulating hydrological function, principally by increasing infiltration, interception, and temporary storage: measures in this category include permeable and porous paving, bioretention cells and rain gardens, vegetated swales, green roofs, expanded urban tree canopy, constructed and restored wetlands, riparian buffer restoration, floodplain reconnection and managed setback of embankments, and the daylighting of culverted watercourses [23,56].

A substantial body of evidence associates such measures with reduced flood vulnerability and with co-benefits for health, amenity, and ecological function [57–63], and the present review finds vegetation cover and green-infrastructure density to be among the most consistently vulnerability-reducing factors across the reviewed corpus.

Regulatory and development-control instruments reduce vulnerability by governing what is built, where and to what standard: these include floodplain overlay districts, setback and freeboard requirements, maximum impervious-surface ratios, on-site stormwater retention and detention standards, minimum green-space provisions in new development, and building-code requirements for ground-floor configuration and flood-resistant materials [64–66].

Conventional engineered measures, including drainage capacity, retention basins, and flood defences, remain relevant but are less directly governed by land-use instruments and are frequently more costly to retrofit. Critically for the purposes of this review, all three categories are represented in the harmonized indicator inventory presented in Appendix A: green-infrastructure density, impervious surface, and area under forest among the sensitivity indicators, and drainage system, preventive structures, and environmental management among the adaptive-capacity indicators, which means their effects can in principle be measured and monitored rather than merely asserted [67,68]. By consolidating these indicators and methods across community, regional, and infrastructure scales, this paper provides land-use planners and policymakers with an evidence-based toolkit for incorporating flood vulnerability metrics into zoning ordinances, floodplain management plans, and land-development review processes.

Appendix A is the operative component of that toolkit. Users select candidate indicators from Tables A1–A4 by vulnerability component and criterion, screen them against locally available GIS, census, and cadastral data, adopt a weighting and aggregation procedure from the method families in Section 4, and calibrate the resulting index against locally observed flood impacts before regulatory use. The inventory supplies candidate indicators and their component assignments; it does not supply transferable weights or thresholds, which this review finds to be context specific.

Vulnerability and resilience are frequently presented as distinct paradigms, and the relationship adopted here requires statement, because the two literatures overlap substantially in what they measure while differing in how they name it [69–71]. This review treats

them as overlapping research traditions rather than as opposed frameworks or as nested constructs and applies three operational rules accordingly.

First, eligibility was determined by measured content rather than by framing vocabulary: a study describing itself as resilience research was included when it quantified vulnerability, susceptibility, fragility, damage, loss, service disruption, coping capacity, adaptive capacity, or recovery, and excluded when resilience was treated only conceptually, as stated in Section 3.3. The converse also applied, since studies framed as vulnerability research were excluded when they quantified only hazard characteristics.

Second, where a source study used resilience as a component within its own vulnerability model, that study's terminology was retained in the presentation of its method, so that readers can match the account given here to the original; the parametric approach of [72], which classifies indicators as exposure, susceptibility, or resilience, and the Integrated Socio-Economic Vulnerability Index of [73], which subtracts a resilience term from exposure and sensitivity, are both reported in Section 4 in their authors' terms. The constituent indicators of those resilience components were nonetheless harmonized to the four components used throughout this review, in most cases as adaptive capacity or coping capacity, since that is the operational role the indicators performed.

Third, resilience was not retained as a fifth indicator domain, because every indicator reported under a resilience heading in the reviewed corpus proved codable to one of the four retained components; retaining it would have duplicated existing categories under a different label rather than capturing an additional construct.

This framing has a boundary that should be stated. The conception of resilience treated here is the one operative in the reviewed measurement literature, in which resilience denotes capacities that offset exposure and sensitivity and is therefore expressed through indicators of the same general kind. It does not encompass the dynamic and systems-theoretic conceptions concerned with recovery trajectories, thresholds, and adaptive cycles over time, which are generally operationalized through system-performance functions rather than through indicator sets and are consequently not represented in the inventory presented in Appendix A. Studies quantifying recovery as a measured outcome were within scope and were included; studies theorizing resilience as a system property without such quantification were not.

Under the IPCC risk framework, exposure and vulnerability are related but conceptually distinct determinants of risk. Exposure refers to the presence of people, infrastructure, assets, or ecosystems in locations that may be adversely affected, whereas vulnerability refers to the propensity or predisposition of exposed elements to experience harm. In this review, reported variables were coded according to the role each performed within its source study, using eight codes: hazard or susceptibility, exposure, sensitivity, adaptive capacity, coping capacity, damage or loss, fragility, and resilience. This is an operational classification and not a theoretical taxonomy. It records how each variable was used by the authors who reported it; it does not assert that the eight concepts are of equivalent kind, nor propose a hierarchy among them.

The distinction is necessary because the reviewed literature does not apply these terms consistently, and either available alternative would distort the evidence: imposing strict theoretical boundaries would require recoding studies whose usage departed from the imposed scheme, thereby substituting the reviewers' conceptual commitments for those of the source authors, while treating the terms as interchangeable would erase distinctions that individual studies did draw. Recording usage as reported preserves that divergence, which is itself among the findings of this review.

Throughout this review, risk is understood as the joint product of hazard, exposure, and vulnerability, and the term is reserved for that composite. Where a source study

describes its output as a flood risk map or risk score, that terminology is retained in reporting the study, since altering it would misrepresent what the authors claim to have measured; such usages should be read as the source study's designation rather than as this review's own. Exposure is treated as an indicator domain within the harmonized inventory rather than as a determinant external to vulnerability, for the reasons given above.

The eight codes occupy three logical levels, which the enumeration above does not distinguish, and which should therefore be made explicit [74–76]. Hazard or susceptibility denotes the flood loading to which elements are subject and is a property of the event and its setting rather than of the exposed element. Exposure, sensitivity, adaptive capacity, and coping capacity denote properties of exposed people, assets, and systems that condition how loading translates into harm [77,78]. Damage or loss, fragility, and resilience denote realized or expected outcomes and the functions relating loading to them, and thus stand at the output rather than the input side of an assessment [12,32,36].

The two compound codes are compound for empirical rather than theoretical reasons: source studies frequently used hazard and susceptibility interchangeably when denoting the propensity of a location to flood, and damage and loss interchangeably when denoting realized consequence, and separating them would have imposed a distinction the source texts did not sustain. Where a study did draw the distinction, the finer usage was preserved in the coding database.

Of the eight codes, four were retained as the principal indicator domains structuring the inventory in Appendix A: exposure, sensitivity, adaptive capacity, and coping capacity. These were retained because they were the components under which indicators were most widely and consistently reported in the reviewed literature. The remaining codes were recorded during extraction and inform the synthesis of method families in Section 4, but do not structure the indicator inventory: hazard-only variables fell outside the review's scope by the eligibility criteria; damage, loss, and fragility are outputs of the models catalogued in Section 4.5 rather than indicator inputs to them; and resilience was harmonized to adaptive or coping capacity as set out above. This coding structure adapts the IPCC framework rather than reproducing it, and departs from it in three respects, which we state explicitly so that readers can relate the inventory in Appendix A to the framework with which they are likely to be familiar.

The principal deviation is the retention of coping capacity as a fourth indicator domain. In the IPCC framework, vulnerability comprises sensitivity and adaptive capacity, while exposure stands alongside hazard and vulnerability as a separate determinant of risk; coping capacity is not an IPCC category [11,79,80]. It derives instead from the disaster-risk-reduction tradition, where it denotes the capacity to absorb, respond to, and recover from an event as it occurs, in contrast to adaptive capacity, which denotes the capacity to adjust in anticipation of expected conditions. The two are frequently conflated, and the temporal distinction between them (before the event as against during and after it) is the basis on which they are separated here. We retained coping capacity because a substantial part of the reviewed literature reports indicators explicitly under that heading, and because merging them would have erased a distinction the source studies drew: the twenty-seven coping-capacity indicators recorded in Appendix A Table A4, including shelter density, local emergency funds, and access to international emergency funds, denote response and recovery resources rather than anticipatory adjustment.

The second deviation is that exposure is treated here as an indicator domain within the harmonized inventory rather than as a determinant of risk external to vulnerability. This reflects the practice of the reviewed corpus rather than a theoretical claim: the great majority of included studies aggregate exposure indicators together with sensitivity and capacity indicators into a single composite vulnerability score, and several of the equations reported

in Section 4 do so explicitly. Excluding exposure from the inventory on IPCC grounds would have made it impossible to represent how those studies constructed their indices.

The third deviation is that component assignments were made study by study according to the operational role an indicator performed, rather than by a single universal rule applied across the corpus. A given indicator may therefore appear under different components in different studies, as documented by the nine indicators receiving more than one assignment among the 226 recorded in Appendix A.

### 3. Methodology

#### 3.1. Review Design and Scope

This study used a structured systematic review design to identify, evaluate, classify, and synthesize quantitative methods for assessing flood vulnerability across community, regional, and infrastructure scales. The review was designed, conducted, and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement [81–83]. The completed PRISMA 2020 checklist is provided in Supplementary Table S1, and the study selection process is reported using the PRISMA 2020 flow diagram in Figure 2.

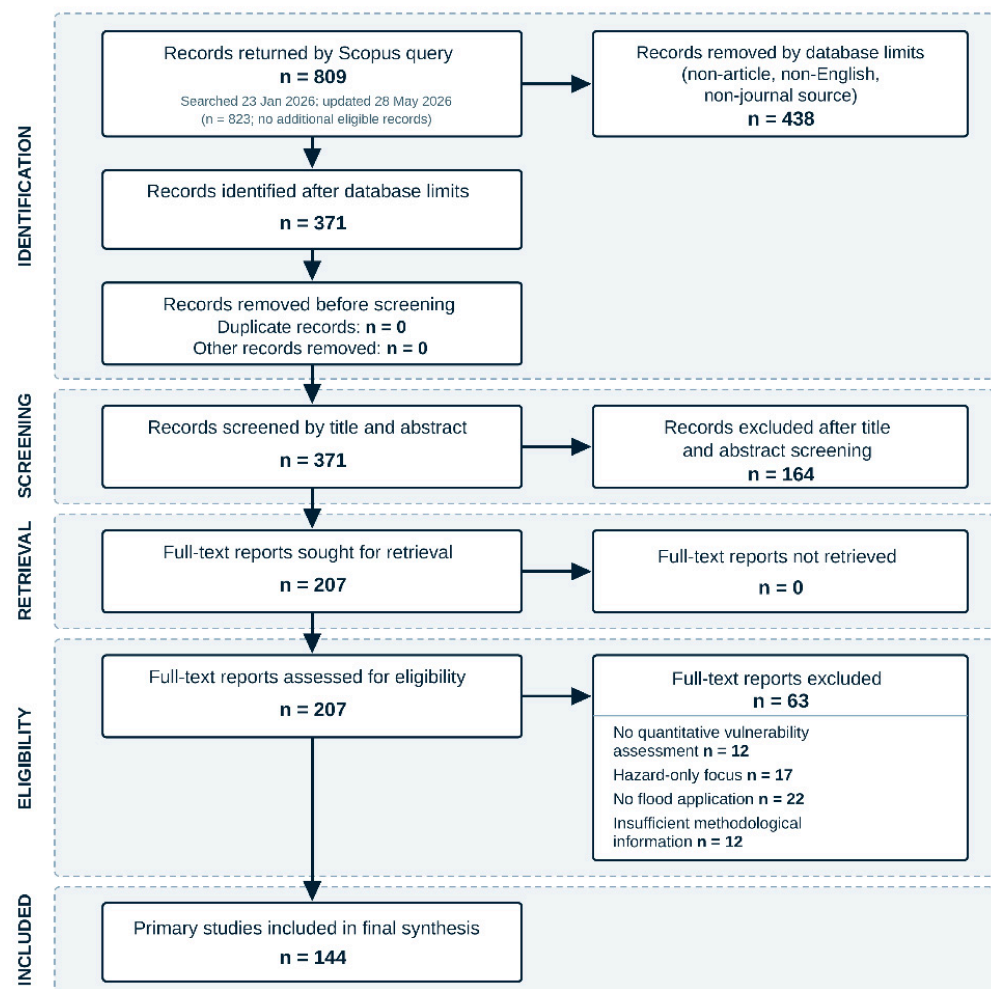


**Figure 2.** PRISMA 2020 flow diagram of study identification, duplicate removal, screening, eligibility assessment, exclusion reasons, and final inclusion.

Because PRISMA was developed primarily for reviews of intervention effects, its items were applied to the present methodological review as a reporting and transparency standard rather than as a template for effect-size synthesis; items relating to meta-analysis, effect measures, and risk-of-bias instruments for clinical designs were reported as not applicable, and the rationale for each such designation is recorded in Supplementary Table S1. A review protocol was prepared in advance of screening and is available from the corresponding author on request; the review was not prospectively registered, as PROSPERO does not accept registrations for methodological reviews of this type. Attention was given to transparent reporting of the search, screening, extraction, coding, and appraisal procedures so that the review process could be independently evaluated and reproduced.

Recent methodological literature emphasizes that systematic reviews should clearly report how records were identified, why studies were included or excluded, how information was extracted, and how disagreements between reviewers were addressed [84–86]. Studies were included only when they quantitatively linked flood conditions to vulnerability, susceptibility, fragility, damage, loss, service disruption, coping capacity, adaptive capacity, or recovery of exposed people, communities, assets, buildings, networks, or infrastructure systems. Studies limited to rainfall forecasting, flood probability, runoff, inundation extent, water depth, or flow velocity without a vulnerability or consequence component were classified as hazard-only studies and excluded. For synthesis, the terminology used by each original study was retained, but each assessed outcome was also assigned a standardized construct code.

The formal review period extended from 1 January 2000 through 31 December 2025. This period was selected on substantive grounds rather than as a conventional interval. The year 2000 approximates the point at which the analytical infrastructure underlying contemporary flood-vulnerability quantification became broadly available to applied researchers: desktop geographic information systems entered widespread use in hazard and planning applications, the first generation of composite social- and livelihood-vulnerability indices was published and began to be adapted to flood contexts, and standardized flood damage- and loss-estimation platforms of the kind catalogued in Section 4.5.3 were released and adopted.

Quantitative flood research published before this point was directed predominantly at hazard characterization, including rainfall, runoff, inundation extent, and flow behaviour, rather than at the vulnerability of exposed people, assets, and systems, and would therefore have been classified as hazard-only and excluded under the eligibility criteria applied here. The closing boundary of 31 December 2025 was set as the last complete publication year available at the time the search was executed, so that the annual publication counts reported in Figure 3 are not distorted by an incomplete final year. This period thus captures the development of contemporary flood vulnerability assessment methods, including composite indices, geographic information systems, statistical models, machine learning applications, infrastructure fragility models, and software based damage assessment tools. The review covered studies that quantified vulnerability at the household, community, urban, regional, building, network, or infrastructure system level. Any changes made after screening began were documented together with the reasons for those changes.

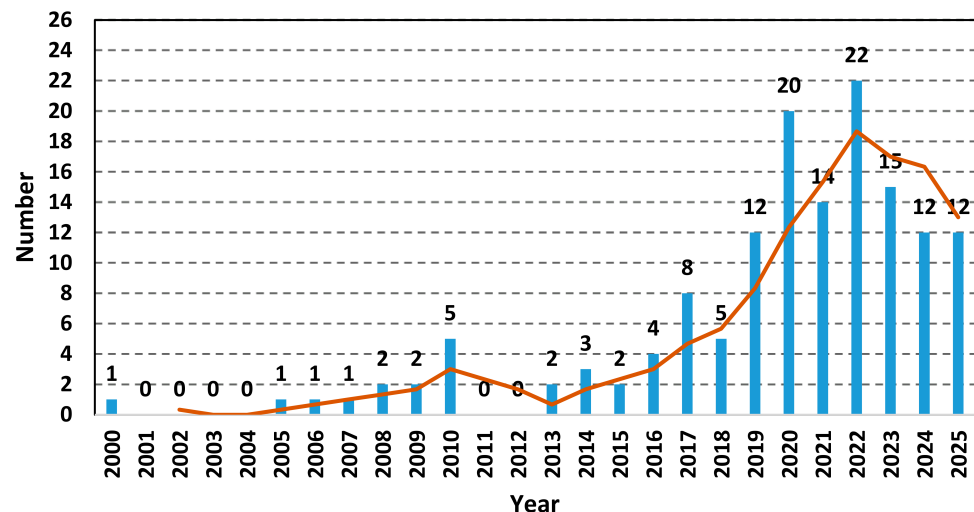


**Figure 3.** Annual publication counts of included studies (2000–2025).

### 3.2. Search Strategy and Reproducibility

The literature search was conducted in Scopus because of its broad coverage of engineering, environmental science, urban planning, disaster risk, construction, geography, and infrastructure research. Scopus was selected as a single source for three reasons. First, it indexes the journals in which the great majority of this literature appears, including those most frequently represented in the included corpus. Second, its coverage spans the six disciplinary areas across which flood-vulnerability research is distributed, which was a requirement given that the review deliberately crosses community, regional, and infrastructure scales that are otherwise served by separate databases. Third, executing a single validated query in one database, rather than adapting syntax across platforms with differing field structures and operators, keeps the search fully reproducible from the string reported below. The sensitivity check described later in this section, in which the strategy was tested against a benchmark set of previously identified studies spanning all three application scales, provides evidence that this design did not systematically exclude a scale or methodological tradition.

The restriction nonetheless has costs, which we state rather than minimize. Single-database searching yields lower recall than multi-database searching, and relevant studies indexed only in Web of Science, Compendex, or discipline-specific repositories such as the ASCE and ICE libraries will not have been retrieved. This falls most heavily on the infrastructure scale, where conference proceedings and technical reports carry a larger share of the evidence than in the community and regional literatures, and it compounds the document-type restriction declared in this section. This is recorded as the first limitation of the review. The initial Scopus search was conducted on 23 January 2026 and was updated on 28 May 2026. Both searches were restricted to studies published between 1 January 2000 and 31 December 2025. The update did not identify any additional records that met the eligibility criteria.

The search was applied to article titles, abstracts, and author keywords. The search strategy was designed to capture studies concerned with community, social, household, regional, building, and infrastructure vulnerability. Infrastructure terminology was therefore included as one component of the search rather than as a mandatory term for every retrieved record.

The final Scopus search syntax was:

TITLE-ABS-KEY (  
flood\*

```

AND
(
vulnerab* OR susceptib* OR fragilit*
OR "adaptive capacit*" OR "coping capacit*"
OR damage* OR loss*
)
AND
(
communit* OR household* OR social OR socioeconomic
OR regional OR urban OR rural
OR infrastructur* OR building* OR transport*
OR utilit*
)
AND
(
quantif* OR assess* OR measur*
OR index* OR indicator* OR model*
OR map* OR GIS OR "machine learning"
OR probabilistic
)
)
AND PUBYEAR > 1999
AND PUBYEAR < 2026

```

In the search syntax, the asterisk (\*) is a truncation wildcard used to match alternative word endings (for example, flood\*). The search string reported above was executed with the following limits applied within the Scopus interface rather than written into the query: document type restricted to journal article, language restricted to English, and source type restricted to journals. On 23 January 2026 the query returned 809 records before these limits were applied; the limits reduced the set to 371 records, which proceeded to title-and-abstract screening. The update executed on 28 May 2026 returned 823 records under the same query, an increase of 14 relative to the January execution; after application of the same limits and screening against the eligibility criteria, none of the additional records met the criteria for inclusion, and the screened set therefore remained at 371. These limits are reported explicitly because the syntax alone returns a substantially larger set, and reproduction of the reported record counts requires that they be applied.

The methods block of the search string included the phrase “machine learning” but did not include “artificial intelligence,” “deep learning,” “neural network,” or related terms. Because the block was disjunctive and also contained the broader terms model\*, assess\*, quantif\*, index\*, indicator\*, and probabilistic, retrieval did not depend on the machine-learning phrase: a study applying artificial-intelligence methods to flood vulnerability would satisfy at least one of the broader terms, since such studies characteristically describe themselves as modelling or assessing vulnerability or susceptibility. The residual risk of non-retrieval is therefore confined to studies that use artificial-intelligence terminology exclusively while avoiding all six broader terms, which we judge to be a small set but cannot quantify without re-executing the search. This omission is recorded among the limitations of the review.

Before the final search was executed, the strategy was tested against a benchmark set of previously identified publications representing community, regional, and infrastructure vulnerability assessment. The search terms were revised until the benchmark studies were successfully retrieved. This sensitivity check was used to reduce the possibility that

the search structure would systematically exclude an important vulnerability scale or methodological tradition.

The benchmark set comprised 38 previously identified studies spanning community-, regional-, and infrastructure-scale applications. The final Scopus search retrieved all 38 benchmark studies (100%), confirming coverage across all three application scales. All benchmark studies were indexed in Scopus.

No restrictions were imposed on journal title, journal quartile, geographic location, study population, or flood type. The formal synthesis included English-language, peer-reviewed journal articles. Original primary research was the predominant document type, but review articles were also eligible where they met the general criteria in Section 3.3, that is, where they reported an original quantitative synthesis, such as a systematically extracted indicator set, a quantified distribution of methods, or a derived classification framework, rather than narrative discussion alone. 13 such reviews met these conditions and are included among the 144 studies. Reviews that did not report original quantitative synthesis were consulted for background and citation chaining but were not counted in the corpus.

Books, technical reports, standards, software manuals, conference papers, government publications, editorials, commentaries, and abstracts were excluded from the formal study corpus but could be cited for technical or contextual information.

Duplicate records were identified automatically using DOI, title, author, and publication year. The reviewers then manually examined records with similar titles or incomplete metadata to identify duplicates that were not detected automatically.

### 3.3. Eligibility Criteria

Studies were eligible for inclusion when they met all of the following criteria:

The publication date was between 1 January 2000 and 31 December 2025.

The study quantitatively assessed flood-related vulnerability, susceptibility, fragility, damage, loss, service disruption, coping capacity, adaptive capacity, or recovery for people, communities, buildings, networks, assets, or infrastructure systems.

The study examined vulnerability at the household, community, urban, regional, building, transportation, utility, or infrastructure system scale.

The study described a reproducible quantification approach, such as a composite index, statistical model, multicriteria decision method, geographic information system, machine learning method, hydraulic or hydrological model, fragility function, probabilistic method, or damage assessment tool, or, in the case of review articles, a reproducible synthesis procedure yielding an original quantitative result.

The study reported sufficient information to identify the indicators, variables, model inputs, weighting procedures, analytical relationships, or damage measures used in the assessment.

The publication satisfied the predetermined language and document type restrictions.

Studies were excluded when they met one or more of the following conditions:

The study assessed rainfall, runoff, flood probability, inundation extent, water depth, flow velocity, or another hazard characteristic without quantifying exposure, vulnerability, fragility, damage, loss, disruption, or capacity.

They discussed flood resilience only conceptually and did not include a quantitative vulnerability or damage assessment.

The study focused exclusively on flood forecasting, rainfall prediction, hydraulic simulation, or emergency communication without linking the analysis to exposed elements, vulnerability, damage, service disruption, or loss.

They did not provide enough methodological information to determine how vulnerability was quantified.

They were editorials, commentaries, abstracts, news articles, or other publication types outside the eligibility criteria.

Their complete text could not be obtained after the retrieval procedures described below.

The distinction between vulnerability and resilience was evaluated according to the operational content of each study rather than title terminology alone. A study framed as resilience research was eligible when it quantified vulnerability, damage, disruption, recovery capacity, or another component directly relevant to the review objectives. Table 2 summarizes the inclusion and exclusion criteria.

**Table 2.** Eligibility criteria used for study identification and selection.

| Criterion Category          | Inclusion Requirement                                                                                                          | Exclusion Condition                                                                                                         | Rationale                                                |
|-----------------------------|--------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------|
| Publication period          | Published from 1 January 2000 through 31 December 2025                                                                         | Published outside the review period                                                                                         | Captures contemporary flood-vulnerability methods        |
| Language and document type  | English-language, peer-reviewed journal article. Review articles eligible where they report an original quantitative synthesis | Conference paper, report, book, editorial, abstract, non-English publication, or review reporting narrative discussion only | Maintains consistent evidence and reporting requirements |
| Flood relevance             | Explicit application to flooding                                                                                               | No flood-related application                                                                                                | Maintains direct relevance to the review                 |
| Assessed construct          | Quantitative assessment of vulnerability, susceptibility, fragility, damage, loss, disruption, coping, adaptation, or recovery | Hazard-only or purely conceptual study                                                                                      | Distinguishes vulnerability and consequences from hazard |
| Application scale           | Household, community, urban, regional, building, network, utility, transportation, or infrastructure-system scale              | No relevant unit or exposed system                                                                                          | Aligns studies with the review objectives                |
| Methodological transparency | Sufficient information on variables, indicators, models, weighting, or damage measures                                         | Quantification procedure could not be determined                                                                            | Enables extraction, comparison, and reproducibility      |
| Full-text availability      | Complete text retrievable through designated procedures                                                                        | Complete text unavailable                                                                                                   | Permits reliable eligibility assessment and extraction   |

### 3.4. Study Selection and Full-Text Retrieval

Two reviewers independently screened the titles and abstracts of all unique records. Each record was classified as eligible, ineligible, or uncertain. Records classified as eligible or uncertain by either reviewer proceeded to full-text assessment to reduce the possibility of excluding relevant studies during the initial screening stage. No dedicated systematic-review management software, such as Covidence or Rayyan, was used. Screening was administered through structured spreadsheet tabulation, with one row per record and separate decision fields for each reviewer, recorded independently and used to compute Cohen's  $\kappa$ . No automated or machine-assisted prioritization, classification, or relevance-ranking was applied at any screening stage.

The same two reviewers independently evaluated the complete text of each potentially eligible study. Full-text decisions were based on the eligibility criteria described above. Each excluded publication was assigned one primary reason for exclusion. Of the 207

full texts assessed, 63 were excluded: 22 had no flood application, 17 had a hazard-only focus, 12 contained no quantitative vulnerability assessment, and 12 provided insufficient methodological information to determine how vulnerability was quantified. No full text proved unretrievable. Counts by reason are reported in Figure 2. Reasons included absence of quantitative vulnerability assessment, hazard only focus, absence of flood application, insufficient methodological information, ineligible publication type, duplicate study population or analysis, and unavailable complete text.

When an article was not available through the publisher or the authors' institutional library subscriptions, the reviewers searched institutional repositories, author repositories, and other legally accessible academic sources. The corresponding author was contacted when necessary. A publication was classified as unavailable only after all designated retrieval procedures had been completed. The number of reports that could not be retrieved is presented separately in the study selection diagram.

Disagreements during title and abstract screening or full-text assessment were resolved through discussion. When the two reviewers could not reach agreement, a third reviewer examined the record and made the final determination. Agreement between the two reviewers was calculated separately for title and abstract screening and full-text assessment using Cohen's kappa. Inter-reviewer agreement was almost perfect during title-and-abstract screening (Cohen's  $\kappa = 0.82$ ) and substantial during full-text assessment (Cohen's  $\kappa = 0.76$ ), interpreted according to the benchmarks of [87].

Cohen's  $\kappa$  was computed over all 371 records at title-and-abstract screening and over all 207 reports at full-text assessment; both stages were double-screened in their entirety. The higher coefficient at the earlier stage reflects the different nature of the two decisions: title-and-abstract screening is a coarse binary judgement over a record set in which most records are clearly irrelevant, which raises expected agreement, whereas full-text assessment applies seven detailed eligibility criteria to records already judged plausible, where borderline cases are concentrated.

### 3.5. Data Extraction

A standardized data extraction form was developed before formal extraction and was pilot tested using included studies representing different scales and methodological approaches. The form was revised after pilot testing to improve clarity and ensure that the same variables could be applied to community, regional, and infrastructure studies. Extraction was a manual process. Each included full text was read and coded by hand against the standardized form; no automated extraction, text-mining, natural-language-processing, or large-language-model assistance was used at any stage of data collection, coding, or indicator harmonization. This decision reflected the nature of the extracted information, much of which (the operational definition of a construct, the conceptual role assigned to an indicator, the basis of a weighting procedure) is expressed discursively across the methods and results sections of a study rather than in a form amenable to automated retrieval. Extraction was conducted independently by two reviewers. Disagreements were resolved through discussion, and cases that could not be resolved were referred to the third reviewer, following the procedure applied at screening and at indicator harmonization. Extracted records were compiled in a spreadsheet-based coding database structured so that each row corresponded to one included study and each column to one extraction field, with the indicator-level coding dictionary maintained as a linked record.

The following information was extracted from each included study:

Author and publication year

Publication venue

Study country and geographic setting

Flood type  
 Spatial scale and unit of analysis  
 Study design and data source  
 Definition of vulnerability  
 Vulnerability components considered  
 Indicators and variables  
 Quantification method  
 Normalization method  
 Weighting and aggregation procedure  
 Software or analytical platform  
 Validation procedure  
 Sensitivity or uncertainty analysis  
 Principal findings  
 Reported limitations  
 Land use, planning, policy, or infrastructure implications

Studies were classified according to three application scales: community, regional, and infrastructure. Community studies evaluated households, demographic groups, neighborhoods, districts, social systems, or livelihood conditions. Regional studies examined spatial units such as watersheds, municipalities, provinces, coastal zones, or national territories. Infrastructure studies assessed buildings, roads, bridges, water systems, power systems, communication networks, schools, or interconnected infrastructure systems.

A study could be assigned to more than one application scale when its analysis explicitly addressed multiple units or systems. Such studies were counted once within each applicable scale rather than assigned to a single dominant scale. The application-scale categories are therefore not mutually exclusive and are not a partition of the corpus: their frequencies sum to more than the 144 included studies, and percentages computed on them represent the proportion of included studies exhibiting a given characteristic rather than shares of a whole. Similarly, a study could contribute to more than one methodological category when it combined approaches such as geographic information systems, multicriteria decision analysis, statistical modeling, machine learning, or damage simulation.

### 3.6. Indicator Harmonization

The indicator database contained 226 indicator–component assignments. After synonymous terms were consolidated, these assignments represented 217 unique harmonized indicator concepts. An indicator could contribute more than one assignment when different studies used it in different conceptual roles.

Terms were consolidated under one harmonized indicator when they represented the same measurable construct. For example, terms such as older population, elderly population, population aged 65 years or older, and proportion of older adults were grouped when they measured the same age related characteristic. Likewise, percentage of impervious surface, impervious area coverage, and proportion of impervious land were combined when their operational definitions were equivalent.

Indicators that were conceptually related but measured different constructs were retained separately. For example, older population, median age, age dependency ratio, and household dependency ratio were not automatically combined because they represent different demographic measures. Similarly, road density, road accessibility, distance to a road, road condition, and transportation disruption were retained as separate indicators.

Where a study's treatment was ambiguous, three tests were applied in order. First, was the term assigned a value, unit, or data source of its own, distinct from those of the indicators listed beneath it? Second, did it enter the study's own equation, weighting

scheme, or reported results as a separate term? Third, would omitting it leave measured content unaccounted for by the specific indicators? A broad term was retained as a distinct indicator only where the first two tests were satisfied; satisfying the third alone was treated as insufficient, since apparent residual content frequently reflects incomplete reporting rather than an additional measured construct. Two default rules governed the remaining cases: where a broad term functioned only as a heading, the specific indicators were retained and the heading was not; and where a study reported a broad term with no specific indicators beneath it, the broad term was retained, since it was itself the measured quantity. Cases in which the tests gave conflicting answers were referred to the reviewer-consensus procedure described below, and the resulting decision was recorded in the coding dictionary together with its basis, so that consolidation decisions remain auditable.

Repeated appearances of the same indicator within one study were counted once for that study, regardless of the number of equations, models, tables, or study locations in which it appeared. When the same harmonized indicator was reported by several studies, it remained one unique concept, while its frequency was recorded as the number of distinct studies in which it appeared.

Each harmonized indicator was coded according to its original operational role as exposure, sensitivity, adaptive capacity, or coping capacity. The assignment was based on the definition and use of the indicator within the source study rather than the indicator name alone. Source studies varied considerably in how explicitly they defined these components, and a substantial proportion listed indicators under a component heading without defining the component itself. Component assignment therefore followed an ordered decision hierarchy.

First, where a study stated an explicit definition of the component, that definition governed the assignment.

Second, where no explicit definition was given but the indicator appeared under a named component heading, or entered a component term of the study's own vulnerability equation, the assignment followed that structural position within the study's model.

Third, where neither an explicit definition nor an unambiguous structural position was available, the assignment was inferred from the indicator's operational role, specifically the direction of its assumed effect on vulnerability and the stage of the flood-impact process at which it was treated as acting: variables representing the presence or quantity of elements in flood-affected locations were coded as exposure, variables representing the propensity of exposed elements to be harmed were coded as sensitivity, variables representing the capacity to adjust or reduce harm in advance were coded as adaptive capacity, and variables representing the capacity to absorb, respond to, and recover from an event were coded as coping capacity.

Fourth, indicators that remained ambiguous after the preceding steps were resolved through discussion between the two reviewers, and unresolved cases were referred to the third reviewer, following the same procedure used elsewhere in the review. Assignments made under the third or fourth step were flagged in the coding dictionary together with the basis for the decision, so that inferred assignments remain distinguishable from those stated explicitly by the source authors. An indicator could therefore be assigned differently across studies when the original authors used it for different conceptual purposes. These differences were retained in the coding database rather than being forced into a single universal classification.

Two reviewers independently examined the proposed harmonized labels and vulnerability component assignments. Disagreements about synonym consolidation, indicator boundaries, or component classification were discussed until consensus was achieved. Unresolved disagreements were referred to the third reviewer.

A coding dictionary was maintained throughout the review. The dictionary records the original indicator term, harmonized label, operational definition, unit of measurement, vulnerability component, source study, and reason for consolidation or separation.

Application of this procedure produced 217 unique harmonized indicators and 226 indicator–component assignments across exposure, sensitivity, adaptive capacity, and coping capacity. The 226 assignments exceed the 217 unique concepts because nine indicators were assigned to more than one vulnerability component by different source studies and were therefore retained under each role in which they were operationalized. Appendix A (Tables A1–A4) presents the complete set of assignments by component. The underlying coding dictionary, which records the original indicator term, harmonized label, operational definition, unit of measurement, vulnerability component, source study, and reason for consolidation or separation, is available from the corresponding author upon request.

### 3.7. Methodological Quality Appraisal

Peer reviewed publication was treated as a minimum eligibility requirement rather than evidence that every study had equivalent methodological quality. Because the review included diverse approaches, such as composite indices, statistical models, geographic information systems, machine learning methods, fragility functions, hydraulic models, and software based damage tools, a tailored appraisal framework was used instead of a single design specific instrument.

Each included study was evaluated across the following domains:

- Clarity of the vulnerability definition
- Transparency of data sources
- Justification of indicator selection
- Clarity of normalization procedures
- Justification of weighting and aggregation
- Appropriateness of the analytical method
- Validation against observed or independent data
- Treatment of uncertainty or sensitivity
- Reproducibility of the analytical procedure
- Consideration of spatial and temporal transferability
- Reporting of limitations

Each domain was rated as 0 when it was absent or inadequate, 1 when it was partially reported, and 2 when it was clearly and adequately reported. Domain scores were used to describe the strengths and weaknesses of the evidence base. Methodological appraisal was conducted independently by two reviewers using the same 11-domain scoring framework. Disagreements in individual domain ratings were resolved through discussion and consensus; cases that could not be resolved were referred to a third reviewer for adjudication. A formal inter-rater agreement coefficient was not calculated for the appraisal stage because the domain scores were used descriptively to characterize the evidence base rather than to determine study inclusion, exclusion, or weighting.

They were not used as automatic exclusion criteria because the purpose of the review was to document the full range of methods used in flood vulnerability research. No minimum score threshold was established at any point, and no study was excluded on the basis of its appraisal score; peer-reviewed publication remained the sole quality-related eligibility condition. Two considerations governed this decision. First, the deficiencies the appraisal measures are themselves among the review’s findings: excluding studies that do not justify their weighting procedures or report a validation strategy would have removed the evidence for the conclusion that such reporting is uncommon. Second, the

instrument is a tailored framework constructed for this review rather than a validated risk-of-bias tool, and no empirical basis exists for setting a defensible cut-off on it. Readers should note the consequence for interpretation: because appraisal scores did not filter or weight the synthesis, frequency counts and method distributions reported in Section 4 treat well-reported and poorly reported studies equally. Appraisal outcomes are therefore reported alongside the synthesis as a characterization of the evidence base rather than as a qualification of it, and this is recorded among the limitations.

### 3.8. Evidence Synthesis

The substantial variation in study populations, spatial scales, flood types, vulnerability definitions, indicators, weighting methods, outcomes, and validation procedures prevented meaningful statistical pooling. A meta-analysis was therefore not conducted. Instead, the evidence was synthesized using descriptive, thematic, and comparative methods.

Descriptive synthesis was used to summarize publication year, geographic distribution, study type, application scale, vulnerability components, indicators, and quantification methods. Thematic synthesis was used to organize the evidence into community, regional, and infrastructure vulnerability. Comparative synthesis was then used to examine differences in data requirements, assumptions, indicator selection, weighting, aggregation, validation, uncertainty treatment, transferability, and decision making relevance.

Methods were coded into non-mutually exclusive families: composite and index-based methods, multicriteria decision analysis, statistical and probabilistic methods, machine-learning methods, hydrological and hydraulic models, fragility and reliability models, and damage or loss models. GIS and named software packages were recorded separately as analytical platforms rather than as independent method families. These families were not treated as mutually exclusive. A study that combined a mathematical index with geographic information system mapping or machine learning validation was coded under every applicable category.

All frequency calculations were based on distinct studies rather than the number of times a method or indicator was mentioned within an article. A study was counted once within each specific method, algorithm, or software category, although it could contribute to several categories. The rule applied throughout is therefore: once per study per category, but potentially in several categories. This applies equally to application scale, method family, analytical platform, and vulnerability component. Consequently, the total frequencies across categories may exceed the total number of included studies, and percentages may not sum to 100 percent.

## 4. Results and Analysis

This section first summarizes the distribution of the included studies and presents the conceptual framework and harmonized indicator inventory. It then reviews community-, regional-, and infrastructure-scale quantification approaches, followed by general mathematical, machine-learning, and software-supported methods. Cross-cutting issues related to indicator selection, weighting, validation, uncertainty, transferability, and planning relevance are synthesized in the Discussion.

### 4.1. Distribution and Characteristics of the Included Studies

Figures 3 and 4 present two aspects of the 144 included studies. Figure 3 shows their annual distribution from 2000 through 2025. Output is low and irregular from 2000 to 2015: no year in that period contributes more than five studies, six years contribute none, and the sixteen years together account for 20 studies, or 13.9 percent of the corpus. A sustained expansion follows from 2016, with annual counts rising from four in 2016 to twelve in 2019

and twenty in 2020. From 2019 onward the series remains at a substantially higher level, with annual counts between twelve and twenty-two and a mean of approximately sixteen; the six years from 2020 to 2025 alone account for 95 studies, or 66.0 percent of the corpus. This growth is consistent with the methodological developments documented in this review, particularly the diffusion of geographic information systems, the consolidation of composite index frameworks, and the more recent adoption of machine-learning approaches.

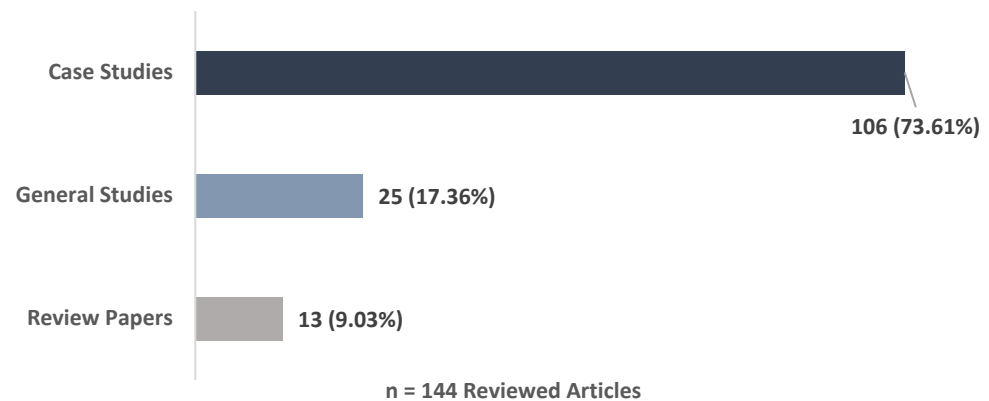


**Figure 4.** Distribution of the 144 included studies by study type.

Two features of the recent series warrant comment. The first is the dip to fourteen studies in 2021, which lies between counts of twenty in 2020 and the series maximum of twenty-two in 2022 and is therefore year-to-year variation rather than a change in trajectory. The second is the more gradual easing across the final years, from twenty-two in 2022 to fifteen in 2023 and twelve in each of 2024 and 2025. This should be interpreted with the completeness of the sampling frame in mind rather than as evidence of declining research activity. Bibliographic indexing lags publication, and records continue to be added to Scopus for an extended period after an article appears, so the most recent years of a search executed in January 2026 and updated in May 2026 are systematically less complete than earlier years. The three-year moving average, which rises to 18.7 in 2021 and remains between 16.3 and 18.7 through 2023 before easing to 13.0 in 2024, indicates a plateau at an elevated level rather than a return toward earlier output. The terminal years of Figure 3 should accordingly be read as a lower bound on output in those years.

Figure 4 shows the distribution of included studies by type. Of the 144 studies, 106 (73.61 percent) are case studies, reflecting the tendency for flood vulnerability to be assessed within specific communities or regions of interest; 25 (17.36 percent) are general or technical studies; and 13 (9.03 percent) are review articles, highlighting the need for more comprehensive synthesis of the body of knowledge on flood vulnerability [30,31]. The included studies and their principal characteristics are listed in Table A5.

Considered as a body, the included studies show several consistent characteristics. Geographically, the corpus is dominated by studies from East and South Asia, particularly China, India and Iran, followed by Europe and North America, with comparatively few assessments from sub-Saharan Africa, South America, Central Asia, and small island developing states. By application scale, the regional and community scales together account for the large majority of the corpus, while infrastructure-scale assessments form the smallest of the three groups; because a study addressing more than one unit or system was assigned to every applicable scale, the scale categories are not mutually exclusive. By method family, composite and index-based approaches predominate at the community scale, geospatial multicriteria decision analysis predominates at the regional scale, and fragility, probabilistic, hydraulic, network-performance and damage models predominate at the infrastructure scale. Among weighting procedures, the analytic hierarchy process and its fuzzy and hier-

archival variants are the most frequently applied (Section 4.5.1); among machine-learning algorithms, principal component analysis is the most frequently applied (Section 4.5.2); and among analytical platforms, geographic information systems are the most frequently applied (Section 4.5.3). Two characteristics recur across the corpus irrespective of scale or method family: independent validation against observed flood outcomes is reported by a minority of studies, and formal treatment of uncertainty or indicator sensitivity is likewise uncommon. These aggregate patterns, rather than study-by-study reporting, form the basis for the methodological appraisal summarized in Section 3.7 and interpreted in the Discussion.

#### 4.2. Knowledge Diagram of Flood Vulnerability

Figure 5 presents the review's conceptual framework, linking standardized flood-related constructs, harmonized indicators, method families, analytical platforms, and application scales.

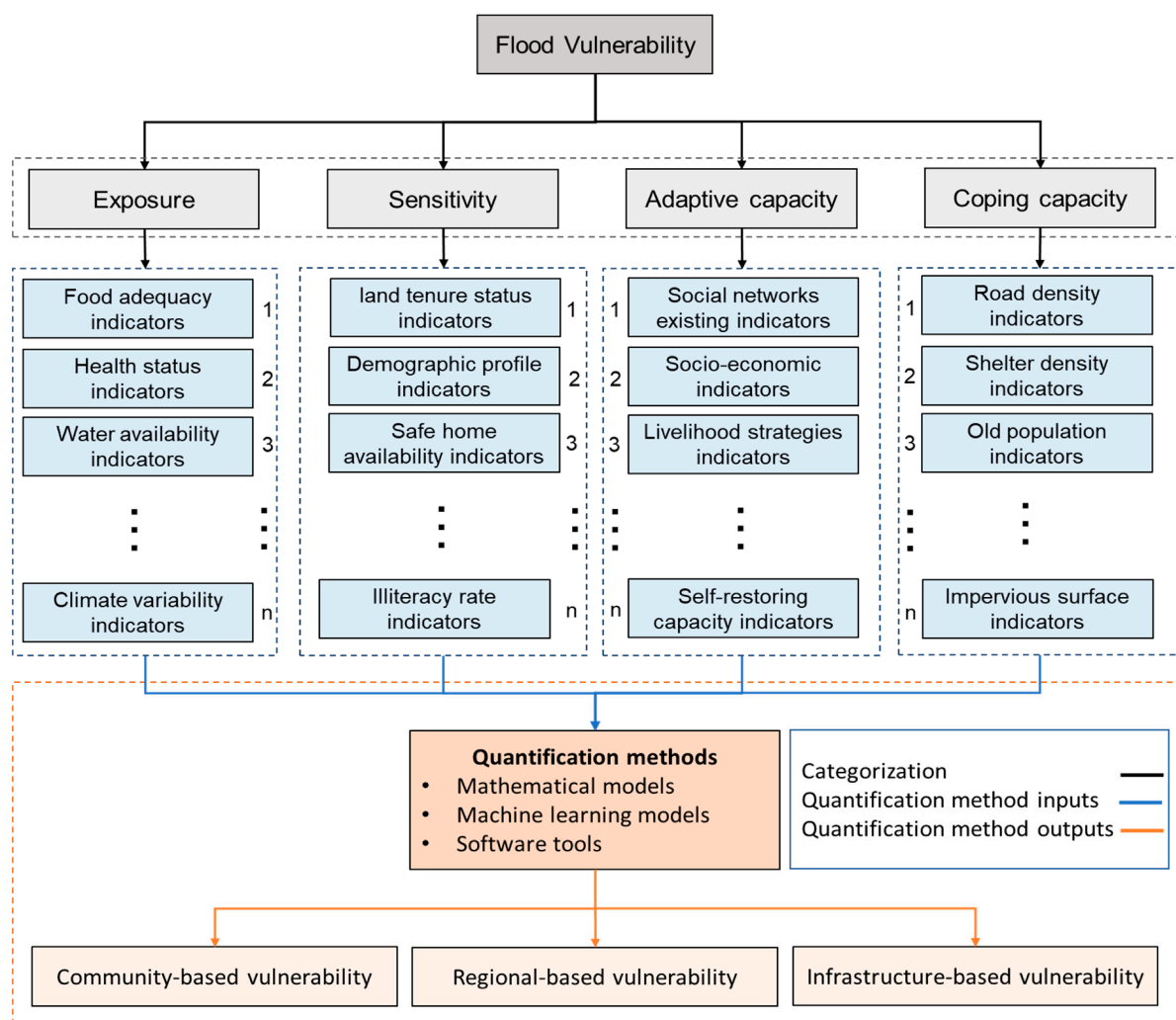


**Figure 5.** Conceptual framework linking flood-related constructs, indicators, quantification methods, analytical platforms, and application scales. Vertical ellipses indicate additional indicators within each component, and  $n$  denotes the number of indicators. The complete indicator inventory is provided in Tables A1–A4.

#### 4.3. Flood Vulnerability Quantification: Indicators

Across the included studies, indicators were derived from census and administrative records, household surveys, interviews and focus groups, remote-sensing products,

hydrological and meteorological datasets, infrastructure inventories, and modeled flood outputs. After harmonization, the database contained 217 unique indicator concepts and 226 indicator–component assignments. Appendix A presents the assignments by exposure, sensitivity, adaptive capacity, and coping capacity.

#### 4.4. Flood Vulnerability Quantification

Existing flood vulnerability quantification methods could be divided into three main categories: community, regional, and infrastructure vulnerability to floods [88,89]. The following subsections provide more details on the different quantification methods used under each of these three categories.

##### 4.4.1. Community-Based Flood Vulnerability Quantification

Across the reviewed literature, community-scale flood vulnerability is quantified almost exclusively through composite indices that aggregate household- or district-level socioeconomic and demographic indicators into a single score, with the livelihood vulnerability index (LVI) and its variants serving as the dominant framework. The methods below differ primarily in how they weight and combine indicators, equal weighting, expert-assigned weighting, or principal-component-derived weighting, rather than in the underlying conceptual structure, suggesting that the field has converged on what to measure for community vulnerability even where it has not converged on how to weight it. Figure 6 shows a summary of the criteria that must be considered to quantify community flood vulnerability [10,16,49,90–94].

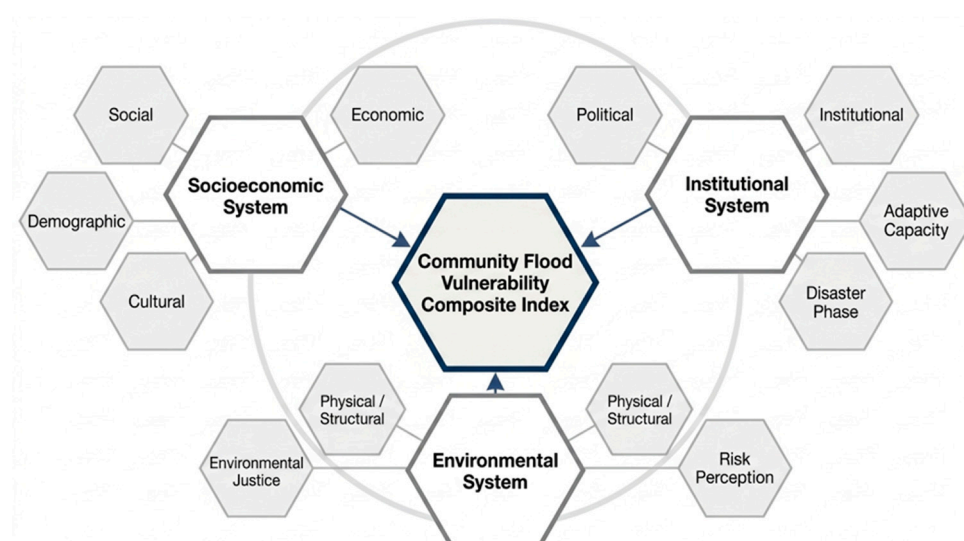


**Figure 6.** Community flood vulnerability criteria.

There are several methods to quantify the main aspects of community vulnerability (i.e., district or household vulnerability), which could generally be represented by the livelihood vulnerability index (LVI). LVI is a composite measure used to assess the vulnerability of communities or households to various environmental, social, and economic risks, such as natural disasters like floods. It combines multiple community indicators that capture different dimensions of vulnerability. The LVI typically draws from factors shown in Figure 7. By aggregating these factors, the LVI provides a holistic view of a community's or household's overall vulnerability, helping decision-makers prioritize interventions to reduce risks and enhance resilience.

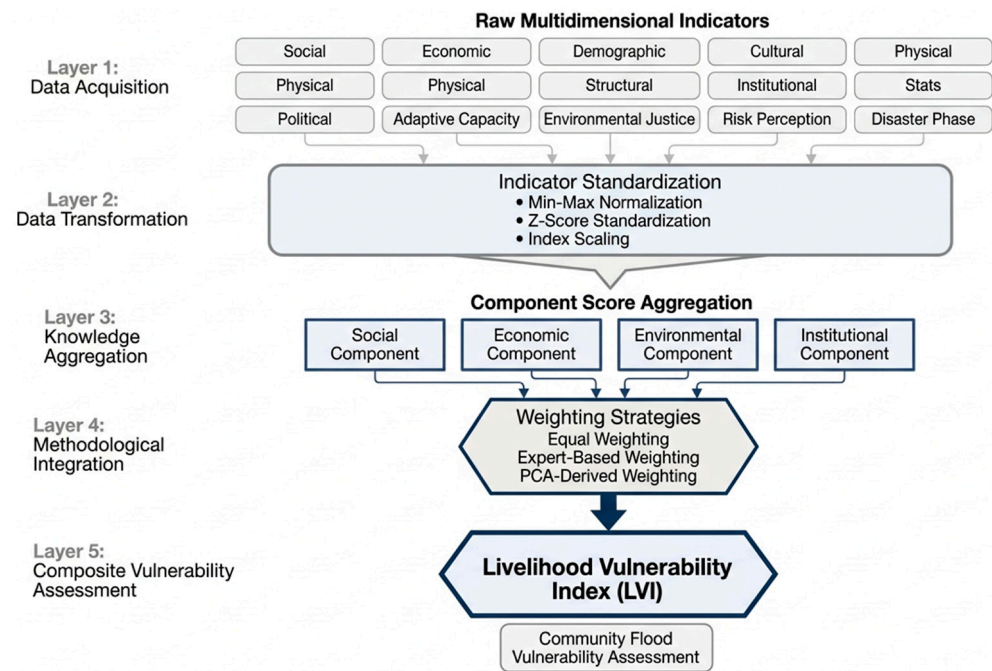


**Figure 7.** Composite index approach in calculating the Livelihood Vulnerability Index (LVI).

One approach for the quantification of the LVI is the composite index approach proposed by [95]. In this approach, each component is quantified by averaging its respective indicators, which are standardized to ensure comparability. The composite index approach then combines these major components to generate a single LVI value, providing a holistic measure of vulnerability that reflects multiple dimensions of livelihood challenges in a community or household. This method helps to highlight specific areas where interventions may be needed to improve resilience.

The study of [96] implemented the composite index approach which was based on the following 10 major components (denoted as  $M_v$ ): natural disasters (i.e., the number of natural disasters that have occurred in the past years), climate variability (i.e., the average standard deviation of the maximum and minimum monthly temperatures and monthly precipitation over a time period), food, water, health, housing and land tenure; socio-economic profile, demographic profile, livelihood strategies, and social networks. Each one of these 10 major components of livelihood  $M_v$  can be obtained using Equation (1).

$$M_v = \frac{\sum_{i=1}^n S_{vi}}{n} \quad (1)$$

Equation (1) demonstrates that each major component is calculated as the average of its  $n$  indicators  $S_{vi}$  when  $n$  represents the total number of indicators within each major component. For a comprehensive list of the different indicators used for each major component, the readers are recommended to check [95,96]. It should be noted that the values of  $S_{vi}$  in Equation (1) are the standardized values of the indicators, which are obtained using Equation (2).

$$IndexS_v = \frac{S_v - S_{min}}{S_{max} - S_{min}} \quad (2)$$

where  $S_v$  is the original value of the indicator,  $S_{min}$  is the minimum value of the indicator, and  $S_{max}$  is the maximum value of the indicator.

Once the values of the 10 major components are obtained, the livelihood vulnerability index ( $LVI_v$ ) can be quantified as the weighted average of the major components as shown by Equation (3).

$$LVI_v = \frac{\sum_{i=1}^{10} MviWmi}{\sum_{i=1}^{10} Wmi} \quad (3)$$

where  $Wmi$  is the weight assigned to each one of the 10 major components; an equal weightage approach is generally followed [96].

A similar method for calculating the LVI is the one that incorporates the IPCC vulnerability definition (which includes exposure, adaptive capacity, and sensitivity), generally referred to as  $LVI(IPCC)_v$ . In relation to that,  $LVI(IPCC)_v$  could be computed using Equation (4) [95]. The  $LVI(IPCC)_v$  ranges from  $-1$  (least vulnerable) to  $+1$  (most vulnerable).

$$LVI(IPCC)_v = (e_v - a_v) \times s_v \quad (4)$$

where  $e_v$  is the exposure component;  $a_v$  is the adaptive capacity component;  $s_v$  is the sensitivity component.

The ten major components mentioned earlier can be utilized to estimate the exposure, capacity, and sensitivity components, as outlined in Equation (4). These components provide critical input data for assessing the vulnerability framework, helping quantify how different factors contribute to overall vulnerability through these three dimensions. More specifically, the exposure component  $e_v$  in Equation (4) could be estimated based on the following major criteria: natural disasters, and climate variability. The sensitivity component  $s_v$  in Equation (4) could be estimated based on the following major criteria: food, water, health, and housing and land tenure. The adaptive capacity component  $a_v$  in Equation (4) could be estimated based on the following major criteria: socio-economic profile, demographic profile, livelihood strategies, and social networks. Each one of the three vulnerability components (VC) is calculated using Equation (5).

$$VC_v = \frac{\sum_{i=1}^q MviWmi}{\sum_{i=1}^q Wmi} \quad (5)$$

where  $Mvi$  are the major components in each vulnerability component,  $Wmi$  is the weight assigned to each major component;  $q$  is the number of major components in each vulnerability component.

Once exposure, sensitivity, and adaptive capacity components are calculated, these three components are combined to calculate  $LVI(IPCC)_v$  using Equation (4).

In addition to the livelihood vulnerability index, social vulnerability is considered one of the causative factors that affect the community vulnerability. In this regard, the Multi-Faceted Composite Social Vulnerability Index (MFCSVI) provides a reasonable baseline for measuring household-level social vulnerability in flood-prone societies as shown in Equation (6) [97].

$$MFCSVI_x = \frac{\sum_{i=1}^n C_n W_n}{n} \quad (6)$$

In this equation,  $MFCSVI_x$  is the Multi-Faceted Composite Social Vulnerability Index,  $C_n$  is the number of key criteria including: socio-demographic C1 (which is comprised of 7 indicators such as number of children, number of elderly people, etc.), physical C2 (which is comprised of 9 indicators such as distance from rivers, flood duration, etc.), financial C3 (which is comprised of 7 indicators such as unemployed head, other economic activities, etc.), health C4 (which is comprised of 4 indicators such as dependency ratio, average distance to nearest health facility, etc.), and social network and social capital C5 (which is comprised of 4 indicators such as network degree density, trusting others,

etc.), and  $W_n$  is the weighting scheme used for the composite index. The study used six different weighting schemes to quantify the composite vulnerability index, including: (W1), a balanced weighting approach for all five key criteria and equal to 0.2, (W2) made socio-demographic C1, with a major effect on vulnerability level with weight equal to 0.6, and other key components equal to 0.1. Likewise, for the remaining weights (W3 to W6), each time one of the key criteria implied a major effect on vulnerability with the weight 0.6 and other key criteria weights equal to 0.1. As a result, six (MFCSVI) were calculated for each household.

Another method to quantify social vulnerability index is based on the principal component analysis (PCA) method, as shown in Equation (7) [16]. The principal components are based on the following 15 indicators: disability, poverty incidence, agricultural labor share, Gini index, vector-borne disease, water-borne disease, social security affiliation, education level, sanitation, drinking water access, power access, road travel time, wall structure, mobile access, and internet access.

$$PCAVulnerabilityIndex_k = \sum_{i=1}^n \left( \eta_i^2 \times PC_{ki} \right) \quad (7)$$

where  $PC_{ki}$  is the normalized transformed matrix of each principal component  $i$  (i.e.,  $PC_{k1}$  is the normalized first principal component transformed matrix), weighted by the corresponding percentage of variance explained ( $\eta_i^2$ ), for each population entity or parish  $k$ . Figure 7 shows the steps of computing the LVI.

Taken together, these community-level methods reveal a consistent reliance on the same underlying data sources, census, household survey, and demographic records, regardless of which weighting scheme or composite formula is applied. This suggests that future improvements to community vulnerability quantification are more likely to come from refining indicator selection and validating weighting schemes against observed flood outcomes than from developing entirely new indices.

#### 4.4.2. Region-Based Flood Vulnerability Quantification

Quantifying flood vulnerability in riverine regions and flood-prone areas requires the integration of various geospatial datasets, including those related to river morphology, geology, infrastructure, climate, and topography [98,99]. These datasets must be carefully processed to assess flood hazards. Also, Multi-Criteria Decision Analysis (MCDA) has been widely applied in many studies to evaluate the flood hazard/risk potential (e.g., [10,29]). MCDA methods such as ANP, AHP, TOPSIS, VIKOR, ELECTRE, PROMETHEE, and Fuzzy approaches provide a structured way to analyze multiple alternatives or objectives and rank them according to their preference. For instance, ref. [13] quantified flood vulnerability rate in a flood-prone area based on Analytic Hierarchy Process (AHP) model and the Triangular fuzzy number (TFN) model [100–104].

Based on geospatial data, 18 sub-criteria/indicators were grouped into five main categories that influence flood vulnerability as shown in Figure 8. These indicators were assigned ratings based on the source dataset (e.g., slope: 0 to 2% rated to 0.443, 2 to 4% rated to 0.242, 4 to 6% rated to 0.109, 6 to 8% rated to 0.163, and >8% rated to 0.043, based on ArcMap component of ArcGIS software). The rated data were then converted to raster format, using digital elevation model and inverse distance weighted tools, with pixel values or symbols representing the significance of each indicator. The ordering of these ratings follows from the hydraulic role of each variable, although the values themselves derive from expert pairwise comparison rather than from hydraulic computation. For slope, the inverse relationship between gradient and assigned vulnerability reflects conveyance and residence time: low-gradient terrain reduces flow velocity and drainage efficiency, promoting ponding, prolonged inundation, and greater depth for a given volume, whereas steep

terrain conveys water rapidly downslope and retains it briefly. Flat land is therefore rated most vulnerable and steep land least, notwithstanding that steep catchments generate more rapid runoff upstream—a distinction that matters because the rated variable represents susceptibility to inundation at a location rather than runoff generation within a catchment.

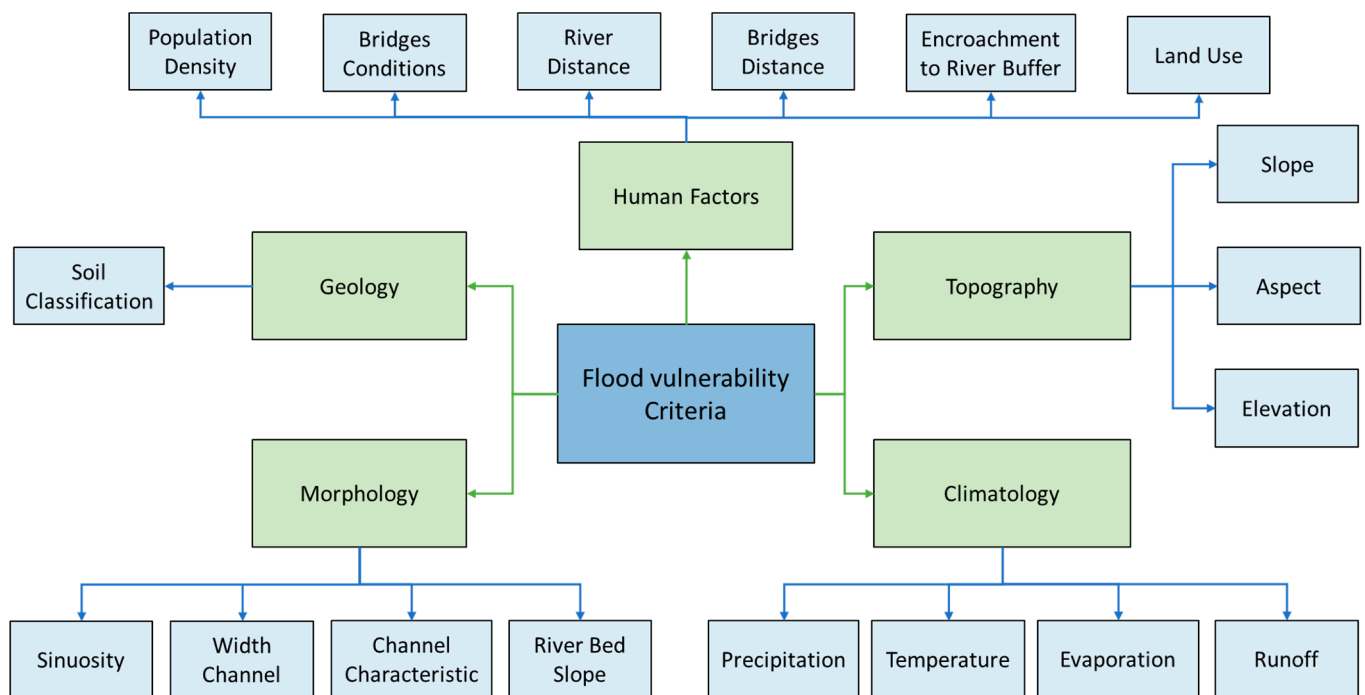


**Figure 8.** The main criteria and sub-criteria of flood vulnerability in riverine areas.

For river morphology, the relevant mechanism is the conveyance capacity of the channel relative to the discharge it receives, and the propensity for flow to leave the channel. Channel width and bed slope jointly determine the discharge a reach can convey before overbank flow occurs; sinuosity increases channel length and flow resistance for a given valley gradient, reducing conveyance and raising upstream water levels; and channel characteristics, including bed material and vegetation, govern roughness and therefore the depth required to pass a given discharge. Reaches combining low bed slope, restricted width, and high sinuosity are consequently rated most vulnerable. The same relationships are expressed deterministically in the Manning-based formulations presented in Section 4.4.3, where conveyance is computed from hydraulic radius, slope, and roughness rather than assigned by rating.

This distinction between mechanism and magnitude should be kept in view. The physical relationships above account for the direction and ordering of the ratings, but the specific values are products of the pairwise comparison matrix elicited from the expert panel for this study area, and would not be reproduced by a different panel or in a different catchment. This is an instance of the calibration dependence discussed in Section 5.

Pixel values are the numerical representation of a specific attribute or characteristic of a geographic area, as captured in a raster dataset. The pixel values of the 18 indicators were ranked from 1 to 9 intensities of the importance level: same, very low, low, relatively low, medium, relatively high, high, very high, and unlimited preference based on AHP and AHP/TFN. Finally, the results of the preference importance level of the pixel values were categorized into five classes (very high, high, moderate, low, and very low) based on equal breaks to determine the class intervals in the Flood Vulnerability Rate (FVR) map, as

shown in Equations (8) and (9). For more information about AHP and AHP/TFN decision analysis methods to classify based on importance level, it is recommended to check [13].

$$FVR_{AHP} = \sum_{i=1}^n (W_i \times V_{AHP}) = 1 \quad (8)$$

$$FVR_{TFN-AHP} = \sum_{i=1}^n (W_i \times V_{TFN-AHP}) = 1 \quad (9)$$

where  $W_i$  is the equal weight of each vulnerability criteria and equal to 0.2,  $V_{AHP}$  is Vulnerability layers based on Analytic Hierarchy Process (AHP),  $V_{TFN-AHP}$  is Vulnerability layers based on Triangular fuzzy number (TFN) and Analytic Hierarchy Process (AHP) and  $i = 1, 2, \dots, n$  is the number of classes. The comparison between the two models is the more informative result. Because the triangular fuzzy formulation admits imprecision in the expert pairwise judgements while the crisp formulation does not, systematic divergence between them would indicate that the resulting classification is sensitive to how expert uncertainty is represented. Where the two produce closely corresponding spatial patterns, the classification is robust to that treatment, and the substantive analytical choices lie instead in the selection and rating of the eighteen criterion layers. This distinction has practical significance, since it identifies where methodological effort yields the greater return: refining the fuzzification of expert judgement matters less than scrutinizing which criteria are admitted and how their classes are rated.

An update of the triangular fuzzy number-based analytic hierarchy process (TFN-AHP) is presented to quantify flood vulnerability named the Game Theory method (GT). The advantage of the GT model is that it can be used as a global flood vulnerability framework and optimization function to minimize the deviation between  $w^*$  and  $w_x$ , which are the nominal and original weights for the  $n$  indicators respectively.

The GT quantification process starts with assigning weights to each indicator of flood vulnerability components such as exposure (which is comprised of 4 indicators such as population density, economic density, building density, farmland density), sensitivity (which is comprised of 4 indicators such as female population, children population, old population, impervious surface), and coping capacity (which is comprised of 4 indicators such as road density, shelter density, old population, impervious surface). The GT combined two types of indicator weights: subjective indicator weights (SW) based on the TFN-AHP, and objective indicator weights (OW) based on Evaluation Measure (EM) methods, as shown in Equation (10) [10].

$$\text{weights for the } n \text{ indicators } w_x = [w_{x1}, w_{x2}, \dots, w_{xj}, \dots, w_{xn}] \quad (10)$$

where  $x$  is equal to two (SW and OW),  $n$  is the number of indicators, and equal to 12. A possible combined weight ( $w^*$ ) which is the merged weights of the SW and OW, can be obtained by Equation (11).

$$w^* = \sum_{i=1}^x \alpha_x w_x \left( \alpha_x > 0 \text{ and } \sum_{i=1}^x \alpha_x = 1 \right) \quad (11)$$

where  $\alpha_x$  is the linear combination coefficient. In the next step, the most satisfactory weight  $w^*$  can be obtained by optimizing function, which is minimizing the deviation between  $w^*$  and  $w_x$  with Equation (12).

$$\text{Min } \left\| \sum_{i=1}^x \alpha_x w_x - w_x \right\|^2, \text{ and } (x = 1, 2, \dots, X) \quad (12)$$

Additionally, according to the differentiation properties of the matrix, the conditions of the optimal first-order derivative are obtained using Equation (13).

$$\sum_{i=1}^x \alpha_x w_i \times w_x^T = w_i \times w_i^T, i = (1, 2, \dots, X) \quad (13)$$

Finally, the flood vulnerability index can be calculated by assigning satisfactory nominal weight  $w^*$  to each indicator of three flood vulnerability components, as shown in Equation (14).

$$FV = \sqrt{\frac{EI \times SI}{1 + CI}} \quad (14)$$

where EI is the exposure value, SI is the sensitivity value, CI is the coping capacity value, FV is the flood vulnerability. In order to identify FV for each region, Equation (15) is used as regional integrated flood vulnerability as follows.

$$RIFVG_j = \sum_{i=1}^m G_i \times \frac{A_i}{S_i}, i = (1, 2, \dots, m) \quad (15)$$

where  $G_i$  is the vulnerability value for grade  $i$ ,  $A_i$  is the area of flood vulnerability,  $s_i$  is the entire area of region  $j$ , and  $RIFVG_j$  is the regional integrated FV grade for region  $j$ . The resulting RIFVG represents the mean FV value for a single region, with a higher RIFVG typically representing a higher vulnerability. Figure 9 shows the steps of the game theory quantification process.

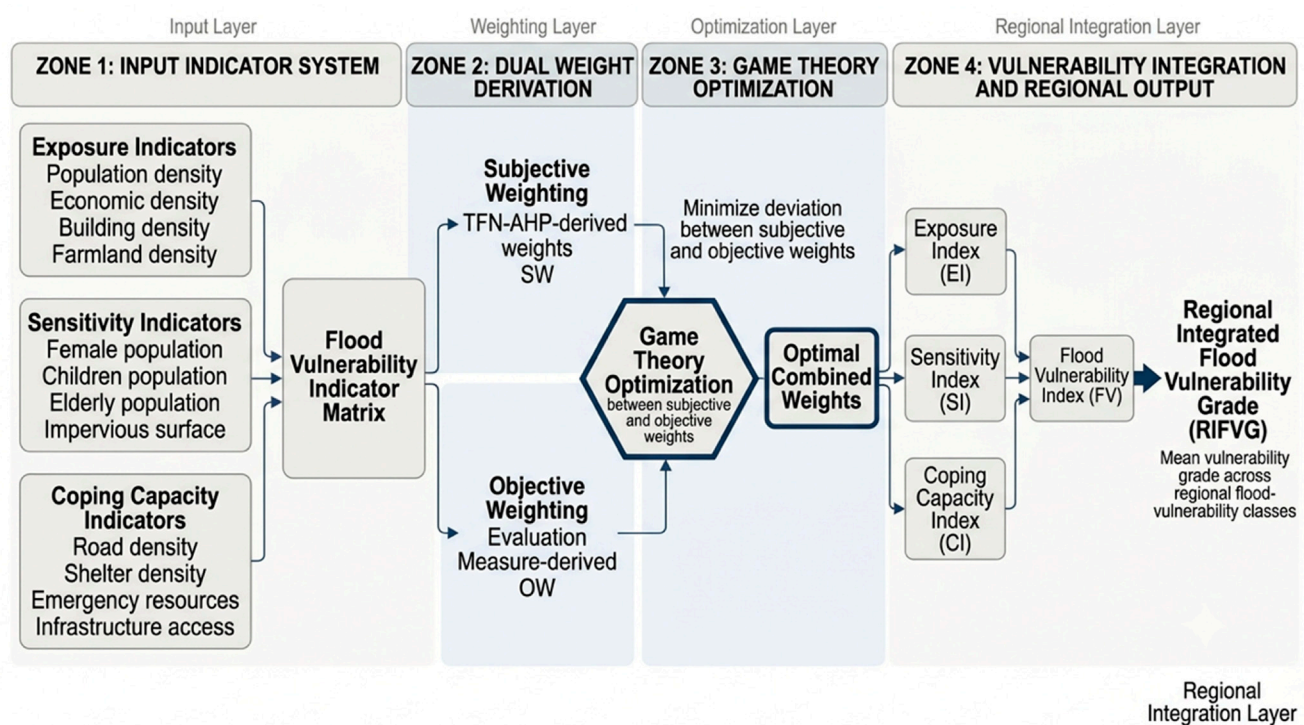


**Figure 9.** The process of determining regional integrated flood vulnerability using game theory.

Satellite-based data on pluvial floods can be integrated with digital elevation methods to quantify flood vulnerability [105]. As an example, ref. [106] quantified flood vulnerability based on a top-down, satellite-based, data-driven assessment of pluvial floods under future climatic and socioeconomic changes over Europe in both urban and non-urban areas, as shown in Equation (16).

$$EVI_i = f(Soc_i, Econ_i, Agr_i) \quad (16)$$

where  $EVI_i$  is the exposure-vulnerability index and the  $Soc_i$ ,  $Econ$ ,  $Agr$  are social, economic, and agricultural components at each geographic location  $i$  (e.g., continent, region and country), respectively. The  $Soc_i$  is comprised of four proxy indicators such as population density, urban population (percentage of total population), age dependency ratio (ratio of population typically not in the labor force aged below 15 and above 64 to those typically in the labor force aged between 15 and 64), and educational level (percentage of the people aged 24–64 with tertiary education). The  $Econ$  is comprised of one proxy indicator, including Gross Domestic Product (GDP) per capita (mitigation ability of individuals and government). The  $Agr_i$  is comprised of one proxy indicator, including percentage of croplands (representing agricultural damages). The social and economic proxy indicators data were obtained from the International Institute for Applied Systems Analysis (IIASA) and the National Center for Atmospheric Research (NCAR), and the agricultural data were obtained from European Soil Data Centre (ESDAC).

The results of the exposure-vulnerability index were distributed as an empirical equation based on three standard weighting methods as follows: equal weights (EW), proportional weights (PW) (according to the number of the proxy indicators in each component), and random weights (RW), which are represented in Equations (17), (18), and (19), respectively [106].

$$EVI_i = 0.33 Soc_i + 0.33 Econ_i + 0.33 Agr_i = \frac{\left[ \frac{Pop_i + UrPop_i + Edu_i + ADR_i}{4} \right] + GDP_i + Crop_i}{3} \quad (17)$$

$$EVI_i = 0.66 Soc_i + 0.17 Econ_i + 0.17 Agr_i = \frac{Pop_i + UrPop_i + Edu_i + ADR_i + GDP_i + Crop_i}{6} \quad (18)$$

$$EVI_i = W_s \times Soc_i + W_E \times Econ_i + W_A \times Agr_i = W_s \times \left[ \frac{Pop_i + UrPop_i + Edu_i + ADR_i}{4} \right] + W_E \times GDP_i + W_A \times Crop_i \quad (19)$$

where  $Pop_i$  is the total population density,  $UrPop_i$  is the proportion of urban population,  $Edu_i$  is the proportion of 25- to 64-year-olds with higher education,  $ADR_i$  is the age dependency ratio,  $GDP_i$  is the GDP per capita,  $Crop_i$  is the average proportion of croplands over all grid cells of each geographic domain (continent, region and country), and  $W_s, W_E, W_A$  are the final random weights (i.e., median of the Monte Carlo runs) for social, economic, and agricultural components, respectively. As the proxy indicators have different units, they were spatially and temporally normalized using a linear min-max rescaling between 0.05 (lowest vulnerability) and 0.95 (highest vulnerability) as two normalization schemes. The spatial and overall normalized indicator values for a given country  $c$ , Equations (20) and (21) are used as shown below.

$$Z_c = \begin{cases} 0.05 + \left( 0.9 \times \frac{X_c - X_{min}}{X_{max} - X_{min}} \right) & \text{for direct relationship} \\ 1 - \left[ \left( 0.9 \times \frac{X_c - X_{min}}{X_{max} - X_{min}} \right) \right] & \text{for indirect relationship} \end{cases} \quad (20)$$

$$Z(c, s, t) = 0.05 + \left( 0.9 \times \frac{X(c, s, t) - X_{min}}{X_{max} - X_{min}} \right) \quad (21)$$

where  $Z_c$  and  $X_c$  are, respectively the normalized and original indicator values for a given country  $c$ ,  $X_{max}$  and  $X_{min}$  are, respectively the maximum and minimum values across all countries,  $Z(c, s, t)$  and  $X(c, s, t)$  are respectively the normalized and original component values for a given country  $c$ , scenario  $s$  (mitigation levels specified by radiative forcing, socioeconomic and combined scenarios) and time period  $t$  (current and future periods), and  $X_{max}$  and  $X_{min}$  are respectively the overall maximum and minimum values across all countries, scenarios, and time periods. For more information about mitigation levels and

radiative forcing, socioeconomic and combined scenarios, the readers are recommended to check [106].

Finally, the values of the  $EVI_i$  are classified into five categories, ranging from very low to very high, with each category representing a quintile of the 0.05–0.95 range. Nine different  $EVI_i$  values were calculated using three distinct weighting schemes and two normalizing methods (one based on spatial normalization and two based on scenario-based normalization). These calculations were performed for each geographic location and mapped to assess flood vulnerability across Europe, both in urban and non-urban areas. The steps are shown in Figure A1.

A parametric approach is one method to quantify flood vulnerability. Ref. [72] quantified river flood vulnerability in the western coastal cities of Mazandaran Province, Iran. Three indices were considered to calculate the flood Relative Vulnerability Score (RVS); technical index (TI), socio-economic index (SEI), and population-environmental index (PEI), which is represented in Equation (22).

$$RVS = (TI + SEI) \times PEI \quad (22)$$

where the technical index, which is comprised of four criteria, includes studies, monitoring, river, and building condition, the socio-economic index, which is comprised of five criteria, includes land use, height distribution, riverside evacuation, training of citizens, and tourism, and population-environment index which is comprised of two criteria includes population density and environmental sensitivity. Each criterion is comprised of several indicators, which belong to the vulnerability components (exposure, susceptibility, and resilience), as shown in Table 3.

**Table 3.** Classification of identified criteria, indicators, and vulnerability components. An asterisk (\*) marks assignment to the corresponding vulnerability component.

| Index                    | Criteria                  | Indicator           | Vulnerability Component |                |            |
|--------------------------|---------------------------|---------------------|-------------------------|----------------|------------|
|                          |                           |                     | Exposure                | Susceptibility | Resilience |
| Technical                | Studies                   | Classification      | *                       |                | *          |
|                          |                           | Urban Detailed Plan | *                       |                | *          |
|                          | Monitoring                | Hydrometry          | *                       |                | *          |
|                          |                           | Meteorology         | *                       |                | *          |
|                          | River                     | Wall Condition      | *                       |                |            |
|                          |                           | Fall Barrier        | *                       |                |            |
|                          |                           | Surveillance        | *                       |                |            |
|                          | Building Condition        | Quality             |                         | *              |            |
|                          |                           | Age                 |                         | *              |            |
|                          | Land Use                  | –                   |                         | *              |            |
| Socio-economic           | Height Distribution       | –                   | *                       |                |            |
|                          | Riverside Evacuation      | –                   | *                       |                |            |
|                          | Training of Citizens      | –                   | *                       |                | *          |
|                          | Tourism                   | –                   | *                       |                |            |
|                          | Population density        | –                   |                         | *              |            |
| Population/Environmental | Environmental Sensitivity | –                   |                         | *              |            |

The scores for each indicator (or criteria without an indicator) were assigned by a panel of experts in environmental management and earth sciences, including specialists in urban planning, natural disaster risk, and hydrology. The scoring range for the lowest level (all indicators or criteria) is between 0 and 10 points, and the highest score was assigned to the less vulnerable situation and vice versa. The result of the RVS was categorized into four classes in the range of 0–700, in which a lower RVS was representative of a higher vulnerability. Finally, the results of the RVS were mapped using the GIS software and the ArcView GIS tool due to their ability to handle and process spatial data to identify flood vulnerability in coastal city areas. Figure A2 shows the steps.

Multiple flood vulnerability assessment is an innovative approach for quantifying flood vulnerability. It accounts for the three key components, exposure, sensitivity, and adaptive capacity, as interconnected systems and evaluates the relationships between them using the Coordinated Development Degree Model (CDDM). This method provides a more comprehensive understanding of flood vulnerability by integrating these components and assessing their combined influence.

The strength of these methods lies in their ability to predict three critical potential scenarios: (1) Potential Disaster Loss (PDL) and Potential Economic Development (PED), (2) Potential Defense Defect (PDD) and Potential Self-organizing Capability (PSC), and (3) Potential Disaster Frequency (PDF) and Potential Resource Waste (PRW). These scenarios offer a comprehensive view of vulnerability, covering economic impacts, defense weaknesses, disaster recurrence, and resource management, enabling better preparedness and response strategies. For example, ref. [12] quantified flood vulnerability levels based on the Fuzzy Comprehensive Evaluation Method (FCEM) and CDDM in the eastern urban area in China. In their study, exposure (which is comprised of 3 indicators such as flow velocity, water depth, and water area), sensitivity (which is comprised of 3 indicators such as population density, economic sensitivity, and agricultural sensitivity), and adaptive capacity (which is comprised of 2 indicators such as early-warning capacity and self-restoring capacity) were considered as the main criterion of flood vulnerability. First, the normalized value of the adaptive capacity, sensitivity, and exposure indicators were calculated by Equations (23), (24), and (25), respectively.

$$AC'_i = \frac{AC_i}{AC_{max}} \quad (23)$$

$$SE'_i = \frac{SE_i}{SE_{max}} \quad (24)$$

$$EX'_i = \frac{EX_i}{EX_{max}} \quad (25)$$

where  $AC'_i$  is the standard value of adaptive capacity,  $SE'_i$  is the standard value of sensitivity,  $EX'_i$  is the standard value of exposure,  $AC_{max}$  is the adaptive capacity maximum of the  $i$ th evaluated indicator,  $SE_{max}$  is the sensitivity maximum of the  $i$ th evaluated indicator,  $EX_{max}$  is the exposure maximum of the  $i$ th evaluated indicator,  $AC_i$  is the adaptive capacity result of the  $i$ th evaluated indicator,  $SE_i$  is the sensitivity result of the  $i$ th evaluated indicator, and  $EX_i$  is the exposure result of the  $i$ th evaluated indicator. In previous studies, the exposure, sensitivity, and adaptive capacity for assessing vulnerability are assumed independent. Very sparse reports exist on flood vulnerability assessment considering the internal relationship among them [44]. Therefore, in the second step, the CDDM method was applied to quantify the relationship between each pair of these three components for multiple flood

vulnerability assessments. For instance, the relationship between exposure and sensitivity, is shown by Equation (26).

$$M_{EX',SE'} = \sqrt{1 - \frac{EX' \times SE'}{(EX'+SE')^2}} \quad (26)$$

where  $SE'_i$  is the standard value of sensitivity,  $EX'_i$  is the standard value of exposure. The relationship between exposure and adaptive capacity, and sensitivity and adaptive capacity were quantified similarly as Equation (26). Afterward, the coordinated development degrees (D) for each urban area were calculated based on Equation (27).

$$D = \sqrt{MT} \quad (27)$$

where D is the coordinated development degree of  $EX'_i$  and  $SE'_i$ , T is the comprehensive evaluation index of  $EX'_i$  and  $SE'_i$  which can be obtained from Equation (28), and M is the coordination degree of  $EX'_i$  and  $SE'_i$ , that can be calculated from Equation (29).

$$T = \alpha * EX'_i + \beta * SE'_i \quad (28)$$

$$M = \left(1 - M_{EX',SE'}^2\right)^2 \quad (29)$$

where  $\alpha$  and  $\beta$  are empirical coefficients,  $\alpha = \beta = 0.5$ ,  $M_{EX',SE'}$  is the coefficient of dispersion of  $EX'_i$  and  $SE'_i$ . The coordinated development degrees (D) were classified into four classes such as huge (H), serious (S), moderate (M), and low (L) for each urban area. Due to three vulnerability components and three possible pair situations for them, the overall six multiple vulnerability situations were proposed. Based on the results of the coordinated development degrees and vulnerability situations, 24 vulnerability assessment and potential scenarios were generated for each urban area, as shown in Table 4 [12]. Figure A3 shows how the multiple flood vulnerability method works.

**Table 4.** The multiple flood vulnerability types and levels in different situations [12].

| Coordinated Development Degree |               | $0 \leq D \leq 0.5$                           | $0.5 < D \leq 0.7$ | $0.7 < D \leq 0.85$ | $0.85 < D \leq 1.00$ |
|--------------------------------|---------------|-----------------------------------------------|--------------------|---------------------|----------------------|
| Coordinated development type   |               | Huge Imbalance                                | Serious Imbalance  | Moderate Imbalance  | Low Imbalance        |
| Overall merit                  | Situation     | Multiple flood vulnerability types and levels |                    |                     |                      |
|                                | $EX_i > SE_i$ | PDL-H                                         | PDL-S              | PDL-M               | PDL-L                |
|                                | $EX_i < SE_i$ | PED-H                                         | PED-S              | PED-M               | PED-L                |
|                                | $SE_i > AC_i$ | PDD-H                                         | PDD-S              | PDD-M               | PDD-L                |
|                                | $SE_i < AC_i$ | PSC-H                                         | PSC-S              | PSC-M               | PSC-L                |
|                                | $AC_i > EX_i$ | PDF-H                                         | PDF-S              | PDF-M               | PDF-L                |
|                                | $AC_i < EX_i$ | PRW-H                                         | PRW-S              | PRW-M               | PRW-L                |

The Bayesian belief network model is supported by a graphical network representing cause-and-effect relationships between different factors considered in a study [23]. The quantitative component of a BBN model is presented with a set of conditional probabilities or probability distributions for each child node, given its parent nodes in the network. Ref. [21] quantified the vulnerability of metropolitan areas to pluvial flooding using BBN probabilistic interfaces for m member of mutually exclusive flood vulnerability variables/indicators (parent nodes) and their data. A total number of 17 variables/indicators

(which is comprised of paved surface (%), vegetation coverage (%), Impervious area (%), Pervious area (%), land cover (%), population density (per km<sup>2</sup>), soil drainage class (well-drained, imperfectly drained, poorly drained, very poorly drained), drainage density (%), Digital Elevation Model (DEM) data (based on height m), rainfall Intensity (mm), and Intensity-Duration-Frequency IDF (the water depth in mm based on the return period of 2, 5, 10, 25, 50, and 100 years in duration equal to 10 min)) were considered as conditional probability  $p(D | V_j)$  data for BBN model, as shown in Equation (30).

$$P(V_j | D) = \frac{p(D | V_j) \times p(V_j)}{\sum_{j=1}^m p(D | V_i) \times p(V_i)} \quad (30)$$

where  $p(V_j | D)$  is the posterior probability of  $V$  (which is comprised of 17 variables/indicators) based on the data or evidence  $D$  (the corresponding data with 17 variables/indicators),  $p(V_j)$  refers to the prior probability,  $p(D | V_j)$  denotes the conditional probability considering  $V_j$  is true, and the denominator is a constant value that represents the total probability, and  $m$  is the number of variables/indicators and equal to 17. The classification of each indicator was based on the available dataset and previous studies. These data or evidence were provided as input data for the BBN Netica software package, and Tree Augmented Naive Bayes (TAN) structure learning was used to validate the data collected. Finally, the BBN model results identified the variables' sensitivity list based on the importance effect level on flood vulnerability. Besides, the results of the BBN model were mapped using GIS software and its ArcMap tool to generate classified urban flood vulnerability maps and predict vulnerable areas for future flood events [44,107–109]. Figure A4 shows the steps of this model.

In order to analyze flood vulnerability, geographic information systems (GIS) are frequently utilized, particularly when assessing susceptibility in metropolitan areas. ArcGIS is a potent GIS tool for quantifying flood vulnerability index. The assessment of the flood vulnerability index, based on the GIS method and ArcGIS tool, is presented in Equation (31) and includes both tangible and intangible criteria related to adaptive capacity component of flood vulnerability [9,110].

$$VI = \frac{\left[ Exp + \left( Sens \frac{\sum_{i=1}^n X_i}{n} \right) + (Adp - Cap \sum_{i=1}^n X_i) \right]}{3} \quad (31)$$

where  $VI$  is the vulnerability index (very low, low, moderate, high),  $Exp$  is the exposure component includes geographical criteria (which is comprised of 1 indicator such as neighborhoods),  $Sens$  is the Sensitivity components includes socioeconomic criteria (which is comprised of 5 indicators such as neighborhoods percentage of the total urban population, percentage of the child urban population, percentage of the elderly urban population, percentage of the educated population, and percentage of the minimum salary), and  $Adp\_Cap$  is the adaptive capacity components in terms of tangible component includes shelter capacity criteria (which is comprised of 3 indicators such as hospital, church, and school) and in terms of intangible components include perception and collective action criteria (which is comprised of 4 indicators such as social construction, previous experience, social network, and action according to the hazard).

The value of each indicator corresponding with vulnerability components are collected through the remote sensing and census data, considering tangible criteria for countable infrastructure that can cope with flood hazards, and intangible components that reflect social activities based on flood risk perceptions and collective action. Finally, flood vulnerability index is quantified by assigning equal weight to each vulnerability component. The results

of the exposure, sensitivity, adaptive capacity, and VI are mapped using the ArcGIS for visualizing flood vulnerability index. Figure A5 shows the steps.

Ref. [73] developed Integrated Socio-Economic Vulnerability Index (ISEVI) to quantify vulnerability of flash flooding events at a regional level in metropolitan settings. Their study effectively quantifies the ISEVI in urban areas by incorporating a comprehensive set of social and economic indicators. Besides, ISEVI was subsequently validated through an uncertainty and sensitivity analysis using the Monte Carlo method. The quantification of the ISEVI based on Latent Class Cluster Analysis is shown in Equation (32).

$$ISEVI = Exposure + Sensitivity - Resilience \quad (32)$$

where *ISEVI* is the Integrated Socio-Economic Vulnerability Index (very low, low, moderate, high, very high), by considering both social and economic dimensions, Equation (32) is expanded as Equation (33).

$$ISEVI = (Soc\ Exp + Ec\ Exp) + (Soc\ Sens + Ec\ Sens) - (Soc\ Res + Ec\ Res) \quad (33)$$

where *Soc Exp*, *Ec Exp*, *Soc Sens*, *Ec Sens*, *Soc Res*, and *Ec Res* are social and economic dimensions of the exposure, sensitivity and resilience components of vulnerability, respectively. For each part of Equation (33), vulnerability was obtained as shown in Equation (34).

$$V_{C_D} = \frac{\sum_{f=1}^n (W_f \times S_f)}{\sum_{f=1}^n W_f} \quad (34)$$

where  $V_{C_D}$  is the vulnerability of a certain component by dimension (exposure, sensitivity, and resilience in both social and economic dimensions),  $S_f$  are the factor scores of the  $n$  indicators in terms of social dimension (which is comprised of 71 indicators such as total population, health centers, elementary schools, retirement homes, etc.) and in terms of economic dimension (which is comprised of 118 indicators such as retirement homes located at flood-prone areas, unemployment rate, per capita income, fixed investments per inhabitant, etc.), and  $W_f$  is the weight of the  $n$  factor based on AHP and PCA. For a comprehensive list of the different indicators used for each major component, the readers are recommended to check [73]. The Monte Carlo method was implemented in the results of the ISEVI to deal with uncertainty and sensitivity analysis of the vulnerability assessment. Afterward, in order to identify possible spatial patterns of vulnerability on a regional scale, a Latent Class Cluster Analysis (LCCA) was conducted, which allowed heterogeneity within a set of urban areas to be identified by dividing them into groups with similar characteristics. Finally, the generated results of the LCCA identified vulnerable parts of the urban areas and allowed vulnerability reduction strategies to be proposed on a regional scale. Figure A6 shows the steps of this process.

In another approach, ref. [111] quantified flood vulnerability in the metropolitan areas using the framework of the social, ecological, and technical system. In their study, flood vulnerability was quantified using an interlinked Social-Ecological-Technological Systems (SETS) framework. This approach involved collecting data on 18 indicators covering the exposure, sensitivity, and adaptive capacity components of flood vulnerability, as shown in Equation (35).

$$V_s = \frac{E_{x1} + E_{x2} + S_{t1} + S_{t2}}{A_{d1} + A_{d2}} \quad (35)$$

where  $E_{x1}$  is the positive effect of the exposure,  $E_{x2}$  is the negative effect of the exposure,  $S_{t1}$  is the positive effect of the sensitivity,  $S_{t2}$  is the negative effect of the sensitivity,  $A_{d1}$  is the positive effect of the adaptive capacity, and  $A_{d2}$  is the negative effect of the adaptive

capacity. The composite vulnerability score  $V_s$  can be in the range between 0 and 1 (0 for least vulnerable and 1 for most vulnerable). For a comprehensive list of the positive and negative effect of each indicator of the vulnerability components, the readers are recommended to check [111]. The vulnerability assessment results for a 500-year return period were mapped using ArcGIS 10.7 tool, and vulnerability flood maps for social, ecological, technological, and a combination of them were generated.

Taken together, the region-based quantification methods reviewed above reveal a shared reliance on geospatial data integration, primarily through GIS platforms and digital elevation models, combined with multi-criteria weighting schemes to generate spatially explicit vulnerability maps [112,113]. The primary methodological convergence across these studies is the use of AHP or AHP-derived weighting frameworks; the primary divergence is in indicator selection, which varies substantially across geographic and climatic contexts. This reinforces the finding that regional vulnerability assessment is more sensitive to context-specific indicator calibration than to the choice of quantification method itself.

Machine learning models are widely used to quantify flood vulnerability. Flood vulnerability in urban areas considering the role of urban districts, based on the Fuzzy Analytic Hierarchy Process method (FAHP), is quantified by Equation (36). The economic, social, and infrastructure is considered as flood vulnerability criteria. To quantify each component, proper indicators are assigned to them as shown in Table 5. The normalized indicators based on min–max method are distributed into 5 classes and based on the FAHP mapped on the urban areas [17]. To assess flood vulnerability a method was designed based on the distance of each neighborhood from vulnerability criteria in the GIS maps. In this regard a grid cell containing one or more vulnerability criteria has the highest degree of importance (red;  $DI = 1$ ). By increasing distance, pixels neighboring this pixel have the second (blue;  $DI = 0.75$ ), third (yellow;  $DI = 0.25$ ) and fourth (white;  $DI = 0$ ) degree of importance, respectively.

$$VuL_r = \frac{\sum_{j=1}^k (DI_k \times A_k)}{\sum_{j=1}^k (A_k)} \quad (36)$$

where  $VuL_r$  is the vulnerability level of  $r$ th neighborhood,  $DI_k$  is the degree of importance for  $k$ th cell of the network, and  $A_k$  is the area of the  $i$ th neighborhood.

**Table 5.** Criteria and indicators for vulnerability mapping.

| Vulnerability Criteria  |                          |                     |
|-------------------------|--------------------------|---------------------|
| Social Indicator        | Infrastructure Indicator | Economic Indicator  |
| Age (<20 & >65)         | Street/Road              | Urban texture       |
| Household Population    | Bridge                   | Urban density       |
| Women population        | Hospital                 | Quality of building |
| Head of women household | Fire station             | —                   |
| Education               | School                   | —                   |
| Tenant                  | —                        | —                   |
| Employment              | —                        | —                   |
| Immigrant               | —                        | —                   |

The proper weight based on the FAHP was assigned to vulnerability assessment results based on Equation (36) for each indicator to generate flood-classified and flood probability vulnerability maps in the urban area.

In a similar approach, ref. [18] used machine learning methods and an indicator-based approach to quantify the Integrated socio-economic vulnerability Index in terms

of regional scale. Their study was based on the CCR-DEA (Charnes–Cooper–Rhodes Data Envelopment Analysis) model and three machine learning models (decision tree, random forest, and gradient-boosted decision trees) to quantify flood vulnerability. The quantification process was based on assessment of the socio-economic vulnerability (SEV) score through the CCR-DEA model and flood susceptibility (FS) score by machine learning models. Besides, the sensitivity and adaptive capacity components of the flood vulnerability were considered to select indicators. The socio-economic vulnerability was quantified by Equation (37).

$$SEV_u = (1 - \theta_u^*) \quad (37)$$

where  $SEV_u$  is the socio-economic vulnerability, which include sensitivity (which is comprised of 9 indicators such as fraction of female population, population density, fraction of main workers in agriculture and cultivation (MAC), fraction of children (below six) population, household density, illiteracy rate, fraction of illiterate female population, fraction of Marginal workers, and fraction of non-working population) and adaptive capacity components (which is comprised of 4 indicators such as fraction of literate female population, fraction of working female population, ratio of literate population to illiterate population, and ratio of working population to nonworking population) of the flood vulnerability framework,  $\theta_u^*$  is the optimal relative efficiency of the  $u$ th Spatial Unit (SU), that is result of the CCR-DEA model based on Equation (38). The spatial unit refers to the urban area's administrative level (e.g., district, village, or block) where indicators data are available.

$$\theta_u^* = \min \left[ \theta_u - \epsilon \left( \sum_{j=1}^x s_j^- + s^+ \right) \right] \quad (38)$$

where  $\theta_u$  is the relative efficiency of the  $u$ th SU,  $s_j^-$  and  $s^+$  are the slack and surplus variables. The optimal value of the  $\theta_u$  corresponding to the socio-economic sensitivity and socio-economic adaptive capacity components can be calculated based on constraints, presented in Equations (39) and (40), and restriction, shown in Equation (41).

$$\sum_{z=1}^Z \lambda_z a_{jz}^{std} + s_j^- = \theta_u a_{ju}^{std} \text{ and } (j = 1, 2, \dots, x) \forall u \quad (39)$$

$$\sum_{z=1}^Z \lambda_z - s_j^- = 1 \forall u \quad (40)$$

$$s_j^- \geq 0 (j = 1, 2, \dots, x), s^+ \geq 0, \text{ and } \lambda_z \geq 0 (z = 1, 2, \dots, Z) \quad (41)$$

where  $a_{jz}^{std}$  is the value of the  $j$ th standardized (based on min–max scale) SEV indicator for the  $z$ th SU,  $x$  is the total number of indicators, and  $Z$  is the total number of SUs. The flood susceptibility value as a result of the machine learning models was estimated by Equations (42) and (43), in order to quantify flood risk score in regional scale (based on geomorphic flood data such as elevation, slope, velocity, duration, flow depth, distance to the nearest stream).

$$\overline{FS}_u = \frac{\sum_{l=1}^L FS_l}{L} \quad (42)$$

$$\overline{FS}_u = \frac{\sum_{k=1}^K FS_k}{K + W} \quad (43)$$

where  $\overline{FS}_u$  is the flood susceptibility score of the  $u$ th SU,  $L$  is the total number of locations in the  $u$ th spatial unit,  $FS_l$  is the flood susceptibility value predicted by the best ML model at the  $l$ th location in the  $u$ th SU,  $L$  is the flood location(s),  $FS_k$  is the flood susceptibility value predicted by the best ML model at the  $k$ th non-waterbody location in the  $u$ th SU,

K and W are the total number of non-waterbody and waterbody locations in the *uth* SU, respectively. Finally, the results of socio-economic vulnerability (SEV) score through the CCR-DEA model and flood susceptibility (FS) score by machine learning models were amalgamated and mapped in GIS platform to generate flood vulnerability maps. The steps of the process are shown in Figure A7.

The Multiple criteria decision-analysis process (MCDA) is an effective method to quantify flood vulnerability due to its ability to identify and compare different flood reduction strategies by assessing their effects. In this regard, ref. [114] quantified flood vulnerability in the urban area based on the MIVES model (the Spanish acronym for the Integrated Value Model for Sustainability Assessment), which is a perspective MCDA and CityGML-based data model. The quantification process was based on identifying indicators for sensitivity (which is comprised of 8 indicators such as state of conservation, the existence of water damage, ground floor typology, the existence of a basement, openings ground floor, roof type, structural material, and facade material) and adaptive capacity (which is comprised of 5 indicators such as drainage system, previous intervention, socio-economic status, number of dwellings, and cultural value) of the flood vulnerability components. Afterward, a value function for each indicator was calculated based on the MIVES model to transform qualitative and quantitative indicators with different measurement units into a dimensionless variable. The MIVES model transforms indicators to a dimensionless variable based on function shapes such as concave, convex, linear, and S-shaped, depending on the nature of the indicator, as shown in Equation (44).

$$V_{ind} = B \times \left[ 1 - e^{-k \times \left( \frac{|X - S_{min}|}{C} \right)^P} \right] \quad (44)$$

where  $V_{ind}$  is the vulnerability indicator value for two requirements; sensitivity and adaptive capacity components and their indicators,  $S_{min}$  is the points of minimum satisfaction and equal to 0,  $X$  is the abscissa that generates a value equal to  $V_{ind}$ ,  $P$  defines the shape of the curve (Concave ( $P < 1$ ), Convex ( $P > 1$ ), or linear ( $P = 1$ )),  $C$  is the  $x$ -value of the point of inflexion for curves with  $P > 1$ ,  $K$  is the  $y$ -value at point  $C$ , and  $B$  is the coefficient of the value functions of the indicators, and it can be calculated by Equation (45).

$$B = \frac{1}{\left[ 1 - e^{-k \times \left( \frac{|S_{max} - S_{min}|}{C} \right)^P} \right]} \quad (45)$$

where  $S_{max}$  and  $S_{min}$  are the points of maximum and minimum satisfaction (0 and 1), respectively, and  $P$  defines the shape of the function curve. The results of the MIVES model provided dimensionless values for each indicator that needed to assign proper weight based on its relative importance. Therefore, the relative importance of different indicators was calculated based on AHP, as shown in Equation (46).

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ a_{21} = \frac{1}{a_{12}} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} = \frac{1}{a_{1n}} & a_{n2} = \frac{1}{a_{2n}} & \cdots & 1 \end{bmatrix} \quad (46)$$

where  $a_{ij}$  represents the relative importance of the indicator  $i$  (sensitivity vulnerability component) with respect to  $j$  (adaptive capacity vulnerability component), on a scale between 1 and 9. Finally, the results of the MIVES model and AHP were mapped into the CityGML-based data model to generate flood vulnerability maps in the urban area.

In another approach, ref. [115] quantified the vulnerability of rural communities to flood events based on an index-based model. In their study exposure, susceptibility, and capacity (resilience) were considered as vulnerability components. The quantification process of the vulnerability is shown in Equation (47).

$$V = W \times S + E + 1 - C \quad (47)$$

where  $W$  is the equal weight for each vulnerability component and equal to one third,  $S$ ,  $E$ , and  $C$  are susceptibility, exposure, and capacity with a range between 0 and 1, and can be obtained from Equations (48), (49), and (50) respectively. In Equation (47),  $(1 - C)$  presents the lack of the capacity. A list of all 43 indicators in terms of exposure, susceptibility and capacity framework can be found in [115].

$$E = \sum_{j=1}^q w_j x_j \quad (48)$$

$$S = \sum_{k=1}^r w_k x_k \quad (49)$$

$$C = \sum_{y=1}^z w_y x_y \quad (50)$$

where  $w_j$ ,  $w_k$ , and  $w_y$  are weights reflecting indicator importance in the sub-components of exposure, susceptibility, and capacity, respectively, and  $x$  is the score allocated to the indicator in the sub-component and is equal to either 1 (low), 2 (medium) or 3 (high). Finally, the vulnerability magnitudes from exposure, susceptibility, and a lack of capacity across communities were quantified, and flood vulnerability maps were generated in the urban areas.

Long-term disaster risk reduction depends on understanding flood impact in terms of vulnerability [116]. Quantifying the vulnerability of urban communities to flood events based on multi-layer indicators is presented in Equation (51) [20,117].

$$V = \sum_{i=1}^n \frac{A_i}{\sum A_i} v_i \quad (51)$$

where  $V$  is the vulnerability in terms of physical, social, economic, environmental, and institutional criteria,  $v_i$  is the multi-layer vulnerability indicator (first layer includes vulnerability to flood events and second layer includes vulnerability indicators which is comprised of 4 indicators such as per-capita GDP, population density, arable land density and road density), and  $\frac{A_i}{\sum A_i}$  is the normalized weight corresponded with  $v_i$  indicator. The results of quantifying vulnerability were classified into five classes using the k-means clustering machine learning algorithm and vulnerability maps were generated.

#### 4.4.3. Infrastructure-Based Vulnerability Quantification

Simulating the vulnerability of critical infrastructure to hazards such as flooding, together with the cascading effects arising from interdependencies among interconnected infrastructure systems, is essential for maintaining critical urban services and strengthening urban resilience [48,118–122]. Two families of method dominate at this scale and are illustrated in the approaches that follow. Probabilistic and reliability-based methods represent infrastructure vulnerability as a probability of failure or service disruption conditional on flood loading, typically through fragility curves derived by Monte Carlo simulation and combined with state-transition models such as Stochastic Petri Nets and Markov chains, as in the assessment of hydroelectric infrastructure by [123]. Hydraulic and hydrodynamic methods instead represent vulnerability through the physical behaviour of the flow and the structures that convey or retain it, using open-channel relationships such as Manning's equation together with continuity and storage-routing formulations, as in the analysis of

channel geometry and gabion-dam mitigation by [124]. Unlike the composite indices that dominate the community and regional scales, both families produce outputs expressed as failure probabilities, damage states, or hydraulic performance measures rather than as dimensionless vulnerability scores. Assessment of flood-induced interdependencies among hydroelectricity-generating infrastructures (applied to water storage concrete gravity dam as a case study), based on the structural-hydraulic modeling, flood frequency analysis, Stochastic Petri Net (SPN) modeling, and Markov Chain analysis is shown by Equation (52) [123].

$$\text{Overall Vulnerability} = P_{fc} \times P_f \times P_{ext} \quad (52)$$

where  $P_{fc}$  is the overtopping hazard probability from the fragility curves analysis,  $P_f$  is the flood occurrence probability from the flood frequency analysis (for example for 100 years = 0.01), and  $P_{ext}$  is the steady state probability from the extended Petri net analysis. The  $P_{fc}$  identifies the probability of failure infrastructure based on water level and was calculated through Monte Carlo simulation under defined different failure conditions. The results of Monte Carlo simulation were rendered to generate fragility curves, which include the probability of infrastructure failure on vertical axis and water level from infrastructure base on horizontal axis. The  $P_f$  is flood occurrence probability and can be calculated by Equation (53).

$$P_f = \frac{1}{T} \quad (53)$$

where  $T$  is the return period for 2, 10, 25, 50, 100, 200, 500, and 1000 years. The  $P_{ext}$  is the value of the predicted risk probability of disruption of the infrastructure performance from extended Petri net analysis based on different levels of the infrastructure performance (e.g., a gravity dam infrastructure comprised of pipelines to transport water from upstream to the downstream area, penstock which is a pipe conduit with large diameter used to deliver the reservoir water to the turbines of a hydroelectric power plant to cause rotation, power plant components which comprised the turbines, shafts, and generators, and transformer substation infrastructure consists of a transformer and overhead lines).

When a storm event has many peaks of a similar magnitude, the channel geometry and other hydraulic properties interact, which might delay or shorten the peak's arrival time and alter the flood peaks' volume. Therefore, considering the effect of increases in vegetation on the various return times of flood events is a valuable strategy for reducing flood vulnerability. In this regard, ref. [124] quantified the impact of changes in the size and location of the gabion dams for examining the mitigation of flood vulnerability. The average cross-sectional velocity  $v$  at a given channel site is given by Manning's relationship, as shown in Equation (54).

$$v = \left(\frac{1}{n}\right) R^{2/3} S^{1/2} \quad (54)$$

where  $S$  is the dimensionless channel slope,  $R$  is the hydraulic radius, which is defined as channel cross-sectional area divided by wetted perimeter and can be calculated by Equations (55) and (56) as follows.

$$A = (bd + zd^2) \quad (55)$$

$$R = \frac{bd + zd^2}{b + 2d\sqrt{z^2 + 1}} \quad (56)$$

where  $A$  is the channel wetted cross-sectional area for a trapezoidal channel with bottom width ( $b$  in m), depth ( $d$  in m), and side slope ( $z$ , dimensionless). At a given cross section, discharge  $u$  is given by Equation (57).

$$u = A v \quad (57)$$

where  $u$  is the discharge of the channel at the cross section ( $\text{m}^3/\text{s}$ ),  $A$  is expressed in  $\text{m}^2$  and  $v$  is expressed in  $\text{m}/\text{s}$ . Stream reaches can be sub-divided into segments representing homogeneous physical properties, with each segment having an upstream inflow and a lateral inflow. The continuity equations for all the segments within a reach are expressed by Equation (58).

$$\frac{dS_i(t)}{dt} = u_{i-1}(t) + q_{Li}(t) - u_i(t) \text{ and } i = 1, 2, \dots, M \quad (58)$$

where  $S$  represents the volumetric storage in each segment ( $\text{m}^3$ ),  $t$  is time (s),  $u$  is the upstream inflow and downstream outflow of each segment ( $\text{m}^3/\text{s}$ ), and  $q$  is the lateral inflow ( $\text{m}^3/\text{s}$ ) for total  $M$  member of segments. The impact of the gabion dam construction on reducing flood vulnerability can be obtained by Equation (59).

$$Q = 1.85LH^{3/2} \quad (59)$$

where  $Q$  is the weir outflow discharge from the dam ( $\text{m}^3/\text{s}$ ),  $L$  is the length of the weir (m), and  $H$  is the increase in water level above the weir height (m). The coefficient 1.85 is dimensional and applies to SI units. The flow over the top of the gabion dam does not occur until all of the storage behind the dam is filled and the height of the water reaches the elevation of the weir ( $h$ ). The value of water storage behind each gabion dam can be calculated by Equation (60).

$$\text{DamStorage} = B \frac{h^2}{2 \tan(s)} \quad (60)$$

where  $h$  is the dam height,  $B$  is the channel width, and bed slope ( $s$ ) expressed for rectangular channel cross sections. The results illustrated that gabion dams could reduce the flood vulnerability by reducing the severity of the initial flood-flow front, increasing the time to peak flow, reducing the discharge of peak flow, and having minor impacts on the flow duration.

Taken together, the infrastructure-based methods reviewed in this subsection rely more heavily on physics-based and probabilistic modeling frameworks, fragility curves, Petri nets, hydrodynamic equations, than the composite-index approaches dominant in community and regional vulnerability assessment [125]. This methodological distinctiveness reflects the engineering origins of infrastructure vulnerability research, and it creates a genuine integration challenge: the indicator frameworks most useful for community and regional planners (composite social and economic indices) are largely incommensurable with the performance-based metrics most useful for infrastructure engineers (failure probabilities, hydraulic loading thresholds). Bridging these two measurement traditions represents one of the most important opportunities for advancing flood vulnerability science at the community-infrastructure interface.

#### 4.5. Flood Vulnerability Quantification: General Methods

Flood vulnerability was quantified by previous studies using different methods. Based on the conducted review of the existing body of knowledge, flood vulnerability quantification rests on two general methodological approaches, mathematical methods and

machine-learning methods, together with the analytical platforms through which both are implemented. These are discussed in greater detail below.

#### 4.5.1. Mathematical Methods

Mathematical methods for quantifying flood vulnerability rely on analytical equations or indices that integrate multiple variables that are perceived to impact flood vulnerability. Mathematical methods are the most diverse and comprehensive as they range from simple indices with a few equally weighted variables to more complex and multi-layered hierarchies that include different variables.

As displayed in Figure 10, AHP, statistical analysis, and index-based methodology are more frequently reported by previous studies because they are widely used in the weight-assigning process of the indicators. As a result, they are more suitable to apply to a specific system for quantifying flood vulnerability. In addition, AHP typically has a broad spectrum of applications, making it a powerful method to deal with a wide variety of vulnerability indicators [13,73,97]. The list of quantification methodologies based on mathematical, hierarchical, and similar deductive, which are used to quantify flood vulnerability, is shown in Figure 10. Table 6 compares the principal method families across criteria relevant to method selection.

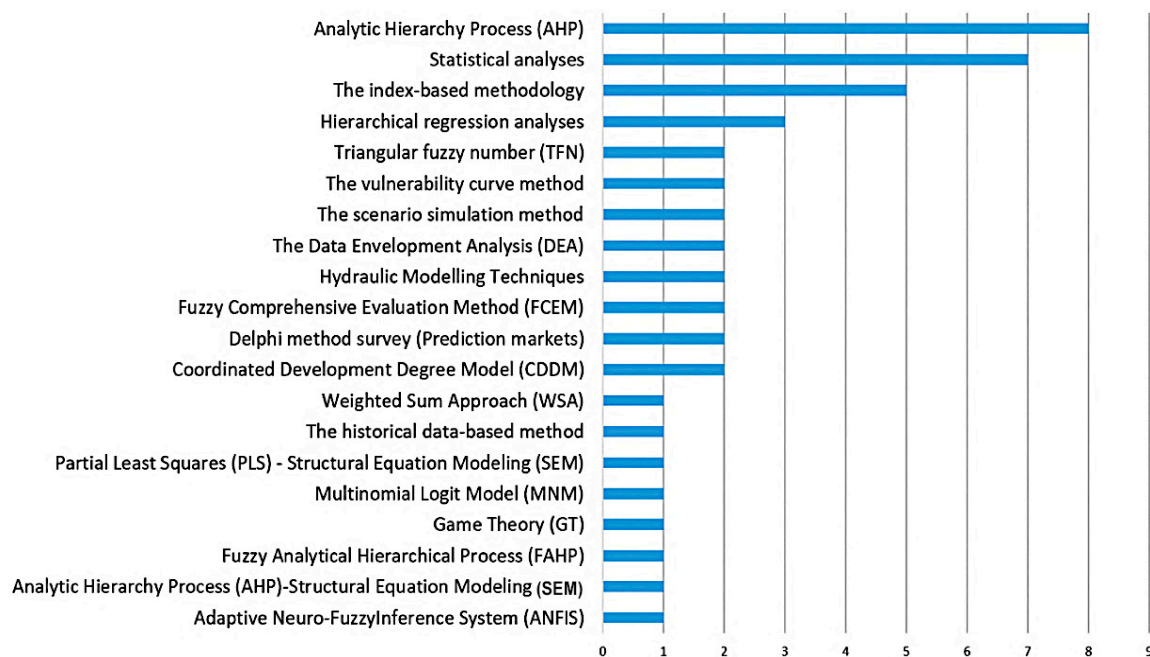


**Figure 10.** Mathematical, hierarchical, and similar deductive methods to quantify flood vulnerability.

**Table 6.** Comparison of the principal flood-vulnerability quantification method families across criteria relevant to method selection.

| Method Family                   | Data Requirement                         | Typical Availability                    | Uncertainty Treatment                            | Implementation Difficulty | Robustness to Missing Data                 | Sensitivity to Parameter Variation                                                                    | Sensitivity to Spatial Scale | Transferability                           |
|---------------------------------|------------------------------------------|-----------------------------------------|--------------------------------------------------|---------------------------|--------------------------------------------|-------------------------------------------------------------------------------------------------------|------------------------------|-------------------------------------------|
| Composite index (LVI, SVI)      | Census or household survey indicators    | High where census infrastructure exists | Rarely formalized/institutional                  | Low                       | Moderate, mean substitution common         | High; scores shift with indicator weights, normalization scheme, and aggregation form                 | High; MAUP affects weights   | Low; weights locally calibrated           |
| MCDA (AHP, fuzzy AHP, TOPSIS)   | Rated criterion layers plus expert panel | Moderate; requires panel                | Fuzzy extensions represent judgement imprecision | Moderate                  | Moderate                                   | High; criterion weights depend on panel composition and pairwise judgements                           | High                         | Low; panel-specific                       |
| Statistical (PCA, regression)   | Complete indicator matrix, many units    | Moderate; needs sufficient <i>n</i>     | Variance explained reported                      | Moderate                  | Low; listwise deletion costly              | Moderate; weights follow from data covariance, but component retention rule is a discretionary choice | Moderate                     | Low; covariance is local                  |
| Machine learning (RF, SVM, ANN) | Labelled outcome data for training       | Low                                     | Cross-validation where reported                  | High                      | Moderate; some handle missingness natively | High; performance varies with hyperparameters, architecture, and train–test partition                 | Moderate                     | Low; encodes training-region distribution |

Table 6. Cont.

| Method Family          | Data Requirement                                | Typical Availability | Uncertainty Treatment             | Implementation Difficulty | Robustness to Missing Data              | Sensitivity to Parameter Variation                                                                                              | Sensitivity to Spatial Scale | Transferability                    |
|------------------------|-------------------------------------------------|----------------------|-----------------------------------|---------------------------|-----------------------------------------|---------------------------------------------------------------------------------------------------------------------------------|------------------------------|------------------------------------|
| Bayesian networks      | Conditional probability tables or training data | Low to moderate      | Native; outputs are probabilities | High                      | High; handles missing evidence natively | Moderate to high; sensitive to network structure and to prior specification where priors are elicited                           | Moderate                     | Moderate; structure may transfer   |
| Fragility/reliability  | Structural and loading data per asset           | Low                  | Native—Monte Carlo standard       | High                      | Low                                     | Moderate; governed by physically constrained parameters, but sensitive to assumed damage-state thresholds and distribution form | Low; asset-level             | Low; encodes construction typology |
| Hydraulic/hydrodynamic | Channel geometry, DEM, roughness, discharge     | Moderate             | Scenario-based                    | High                      | Low                                     | Moderate; roughness coefficients and boundary conditions are the principal sensitivities, but are physically bounded            | Low; physically determined   | Moderate; physical relations hold  |

Note: Entries characterize the methods as applied within the reviewed corpus rather than their theoretical properties and reflect the modal case within each family; individual studies vary. Comparison of method performance by flood mechanism is not reported, as the reviewed studies rarely disaggregate results by flood type.

#### 4.5.2. Machine Learning Method

Capitalizing on the increasingly accessible flood-related data and more powerful computing capability of machines, ML methods have proved to be very effective in learning and recognizing patterns from historical data for estimating flood vulnerability. As shown in Figure 11, nine machine learning algorithms have been reported by previous studies to achieve flood vulnerability quantification objectives. These methods include Principal component analysis (PCA), random forest regressor and classifier (RF), artificial neural networks (ANN), ordinary least squares (OLS), decision tree (DT), K-nearest neighbors (KNN), Bayesian belief networks (BBN), agglomerative hierarchical clustering (AHC), and support vector machine. Among these algorithms, PCA was the most frequently used because it improves the performance of the ML algorithm as it eliminates correlated indicators that don't contribute to any decision making. PCA helps in overcoming data overfitting issues by decreasing the number of indicators [17,126,127].

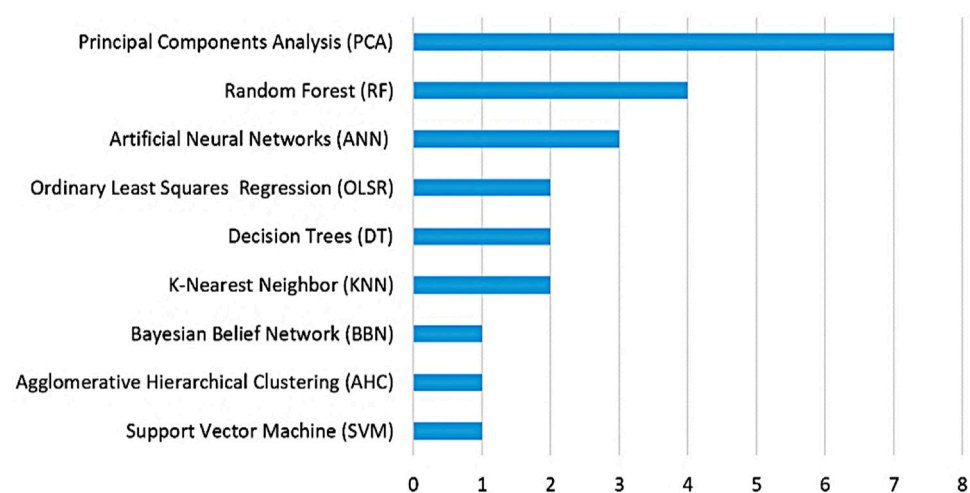


**Figure 11.** Machine learning algorithms for flood vulnerability quantification.

The predominance of principal component analysis warrants explanation, since it exceeds what the general utility of the method would suggest. Four factors account for it. The first, and principal, factor is that PCA addresses a problem intrinsic to composite index construction rather than to prediction. Vulnerability indicator sets are characteristically large and strongly intercorrelated: income, educational attainment, employment status, and poverty incidence measure overlapping aspects of socioeconomic position, and aggregating them without adjustment implicitly assigns greater weight to whatever the correlated group jointly represents. PCA resolves this by deriving weights from the covariance structure of the observed data, as in the variance-weighted formulation of [16] reported earlier in this section. It is therefore adopted in studies whose analytical framework is otherwise entirely index-based.

Three further factors reinforce this. PCA is unsupervised and requires no labelled outcome data. Supervised alternatives, including random forests, support vector machines, and neural networks, require observed vulnerability or damage outcomes against which to train, and such data are seldom available at the spatial units at which vulnerability is assessed; this constraint is the same one that limits independent validation across the corpus. PCA also offers a data-derived alternative to expert weighting that avoids the cost and the subjectivity of convening an expert panel, and several studies adopt it explicitly on that basis, in some cases comparing the two approaches directly. Finally, its outputs are interpretable: component loadings can be inspected and related to the original indicators, which matters where a vulnerability classification must be defended to planning authorities

or the public, and which distinguishes it from the ensemble and neural methods discussed in Section 5.

One qualification should be entered. PCA is counted here within the machine-learning family because the source studies described it as such, but in most of these applications it operates as a weighting and dimensionality-reduction procedure within an otherwise conventional composite index rather than as a predictive learning algorithm. Its frequency should therefore be read as evidence that indicator redundancy is a widely recognized problem in composite index construction, rather than as evidence of extensive predictive machine-learning application in this literature. Restricting the count to genuinely predictive applications would yield a substantially more even distribution across the algorithms shown in Figure 11.

One further approach was not represented among the algorithms identified in this corpus and warrants mention. Maximum entropy modelling estimates the probability distribution of maximum entropy consistent with a set of observed constraints and requires only presence records rather than matched presence and absence observations. This suits flood and waterlogging applications, where inundated locations are recorded but non-inundated locations are seldom systematically observed, and it therefore addresses the labelled-outcome-data constraint identified above as limiting supervised methods in this field. Applications within the review period couple maximum entropy estimation with land-use simulation to identify areas likely to become waterlogging-prone under projected land-use change [83,128], and more recent work extends this by incorporating landscape configuration indices alongside conventional physical predictors [75,129,130]. The absence of this method family from the retrieved corpus reflects a limitation of the search strategy rather than of the literature, since the search terms did not include entropy-based modelling vocabulary; this is noted among the limitations in Section 5.

#### 4.5.3. Analytical Platforms

This subsection reports the platforms through which the methods described above were implemented. Consistent with Table 1, these are execution environments rather than an additional methodological family: they process, store, analyze, and display data according to procedures specified by the analyst, and the same platform supports methods from several families. As shown in Figure 12, previous studies use the GIS method most frequently to quantify flood vulnerability because it processes various systems, including processing, storing, manipulating, analyzing, integrating, and displaying data. GIS quantifies flood vulnerability by assembling information from different maps, aerial photographs, satellite images, and digital elevation models (DEM). Input parameters include flood data, land use, socioeconomic data, and rainfall values [9,28,100].

The concentration of analytical work in geographic information systems raises two questions that should be distinguished. The first concerns reliance on this class of tool, which we do not consider problematic. Flood vulnerability is an intrinsically spatial construct: exposure is defined by location relative to inundation, sensitivity varies across administrative and physical units, and the outputs required by planning authorities are maps. The operations these platforms provide—overlay, proximity and distance computation, zonal statistics, raster algebra, and interpolation—are the operations the reviewed methods require. Their predominance therefore reflects the structure of the problem rather than habit or tool availability.

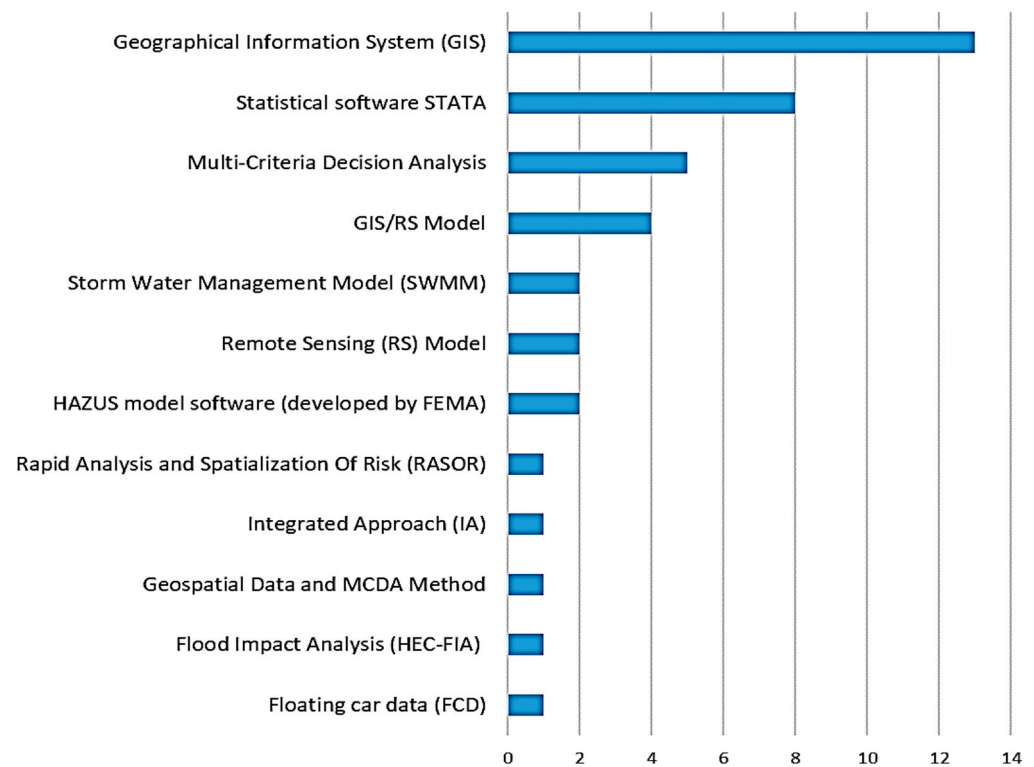


**Figure 12.** Software-based methods to quantify flood vulnerability.

The second question, concerning dependence on a particular proprietary product, is more consequential. As set out in Section 1, the platform does not determine the method: the composite indices, weighting schemes, and classification procedures reviewed here are platform-independent, and the same analysis can be implemented in ArcGIS, QGIS, GRASS GIS, or a scripted geospatial environment. The risks associated with proprietary concentration are therefore not risks to analytical validity but to equity and reproducibility. Licensing costs constitute a material barrier for municipal authorities, academic groups, and agencies in lower-income jurisdictions, which are frequently those facing the highest flood vulnerability, so that the tools most used to assess vulnerability are least accessible where assessment is most needed. Workflows that depend on specific software versions, extensions, and license entitlements are also more difficult to reproduce independently, which compounds the reproducibility limitations identified in this review. And where standard procedures are executed through proprietary implementations, the parameters and defaults applied may not be reported, obscuring precisely the normalization, weighting, and classification choices that this review finds to be inadequately documented across the corpus.

These concerns are readily remediable, since every operation required by the methods reviewed here is available in open-source geospatial software, and several included studies implement their analyses in such environments or in scripted workflows. We suggest that authors report the platform, version, and any non-default parameters used, and that, where the analysis does not depend on proprietary functionality, open implementations be preferred so that vulnerability assessments remain reproducible and accessible to the jurisdictions that most need them.

Figure 12 summarizes the software tools and platforms employed across the included studies, revealing that GIS dominated software-based applications (13 studies), followed by statistical software STATA (8 studies) and Multi-Criteria Decision Analysis platforms (5 studies), while specialized tools such as HAZUS, SWMM, and remote sensing models each appeared in two studies, and the remaining tools were each used in a single study.

Finally, Table 7 presents an exhaustive list of flood vulnerability/loss estimation software, categorized based on data type, country of use, main intensity indicator to measure, and geographical scale to use. More information and details about each software tool can be found in the cited references.

**Table 7.** Global and country-wide flood vulnerability/loss estimation model software.

| Model/Software | Type                    | Country                    | Availability                                            | Main IM<br>(Intensity Measure)                                                                         | Geographical<br>Scale                       | Reference(s) |
|----------------|-------------------------|----------------------------|---------------------------------------------------------|--------------------------------------------------------------------------------------------------------|---------------------------------------------|--------------|
| ANUFLOOD       | Empirical               | Australia                  | Research/<br>institutional                              | Water depth                                                                                            | Regional,<br>National                       | [28,29]      |
| ESTDAM         | Empirical-<br>synthetic | UK                         | Research/<br>institutional                              | Water depth,<br>Flood duration                                                                         | Local, Regional                             | [28,131]     |
| FAT            | Empirical               | Czech Republic             | Research/<br>institutional                              | GIS-based data<br>on flooding                                                                          | Local, Regional                             | [28,132,133] |
| FDAM           | Empirical               | Japan                      | Public agency                                           | GIS-based data<br>on flooding                                                                          | Local, Regional                             | [28,100,133] |
| FLEMO          | Empirical               | Germany                    | Research/<br>institutional                              | Water depth                                                                                            | Local, Regional,<br>National                | [29,131,134] |
| FLODSIM        | Empirical               | South Africa               | Research/<br>institutional                              | GIS-based data<br>on flooding<br>and data extracted<br>from video remote<br>sensing                    | Local, Regional                             | [28,133]     |
| FloodAUS       | Empirical-<br>synthetic | Australia                  | Research/<br>institutional                              | GIS-based data<br>on flooding                                                                          | Local, Regional,<br>National                | [28,135]     |
| HAZUS          | Empirical-<br>synthetic | USA                        | Public agency<br>(FEMA, free)                           | Water depth; Flood<br>duration; Flow<br>velocity; Presence of<br>debris; Rate of rise;<br>Flood timing | Local, Regional,<br>National                | [29,136]     |
| HAZUS-MH       | Empirical-<br>synthetic | USA                        | Public agency<br>(FEMA, free)                           | Water depth; Flood<br>duration; Flow<br>velocity; Presence of<br>debris; Rate of rise;<br>Flood timing | Local, Regional,<br>National                | [28,136]     |
| HEC-FDA        | Empirical-<br>synthetic | USA                        | Public agency<br>(USACE, free)                          | Water depth; Flood<br>duration; Flow<br>velocity; Presence of<br>debris; Rate of rise;<br>Flood timing | Local, Regional                             | [28,137]     |
| HIS-SSM        | Empirical               | Netherlands                | Public agency                                           | GIS-based data<br>on flooding                                                                          | Local, Regional                             | [28]         |
| HWSCalc        | Empirical-<br>synthetic | Germany                    | Research/<br>institutional                              | GIS-based data on<br>flooding, water<br>surface profiles                                               | Local, Regional                             | [28,94]      |
| JRC            | Empirical-<br>synthetic | EU Member<br>States/Global | Open access<br>(published<br>depth–damage<br>functions) | Water depth                                                                                            | Regional,<br>National, Euro-<br>pean/Global | [29,138]     |
| MCM            | Synthetic               | UK                         | Proprietary/<br>licensed<br>(FHRC)                      | Water depth                                                                                            | Regional,<br>National                       | [29,139]     |

Table 7. *Cont.*

| Model/Software | Type                | Country      | Availability                             | Main IM<br>(Intensity Measure)                                                                            | Geographical<br>Scale        | Reference(s) |
|----------------|---------------------|--------------|------------------------------------------|-----------------------------------------------------------------------------------------------------------|------------------------------|--------------|
| MDSF           | Empirical-synthetic | UK           | Public agency<br>(Environment<br>Agency) | GIS-based data<br>on flooding                                                                             | Local, Regional,<br>National | [28]         |
| TEWA           | Empirical-synthetic | South Africa | Research/<br>institutional               | GIS-based data on<br>flooding                                                                             | Local, Regional,<br>National | [28]         |
| USACE          | Synthetic           | USA          | Public agency<br>(free)                  | Water depth; Flow<br>velocity; Duration<br>of inundation;<br>Contamination;<br>Frequency of<br>inundation | Local, Regional,<br>National | [29]         |

Note: Availability categories: public agency, distributed without charge by a government body; open access, functions or data freely published with documented methodology; proprietary or licensed, commercially or contractually restricted distribution; research or institutional, available through the developing institution. Availability terms vary over time and between jurisdictions, and current conditions should be confirmed with the distributing organization.

## 5. Discussion

There are two main divisions in academic study on vulnerability to floods. One approach, which includes most of the studies (more than 73 percent), is case studies that used one of the general methodologies as applications to quantify flood vulnerability. In this approach, data are gathered from post-flood disaster events and used to offer a thorough understanding of vulnerability processes, interactions, and outcomes that are location- and hazard-specific. However, using results from a few individual case studies to make comprehensive generalizations based on the dynamic concept of vulnerability may yield unreliable conclusions. The second group is the general methods, which concentrate on developing, mapping, and analyzing quantitative indicators. A few studies in the second category used different methods to quantify vulnerability to floods and compared the results to evaluate finding validation [12,17,18,21,114,140].

The predominance of case studies is not itself a deficiency, since flood vulnerability is context-specific and locally calibrated assessment is appropriate. What limits comparability is the absence of common reporting baselines. We therefore recommend three: that indicators be reported with their operational definitions and units of measurement, so that equivalence between studies can be established; that indicator weights and the procedure generating them be reported separately from the resulting scores, so that the effect of weighting can be isolated; and that unnormalized component values be reported alongside composite indices, so that exposure, sensitivity, and capacity contributions remain recoverable. These are reporting requirements rather than methodological prescriptions and would render case-study findings cumulative without constraining the local calibration that the evidence reviewed here shows to be necessary.

The results of this study highlight several gaps in knowledge regarding the quantification of vulnerability. Assessment of selecting indicators, enhancing the quantifiability of influential indicators, understanding interaction between indicators, and using proper methodologies are among the top research priorities for quantifying vulnerability.

### 5.1. Indicator Selection and Indicator Interaction

The selection process of drivers and indicators is mainly based on previous studies. However, considering the dynamic concept of flood vulnerability in different places and its dependence on the time of the event, their prioritization may differ from one study to

another [32,141,142]. Besides, it is possible to not consider indicator(s) in the quantification process of flood vulnerability, and consequently, it may affect validation of the final results [27]. Therefore, a comprehensive framework that includes all possible drivers and indicators of flood vulnerability is necessary to avoid unreliable conclusions. In another approach, several researchers choose flood vulnerability indicators using prepared frameworks such as IPCC and UNDRR. Two guidelines follow from the evidence assembled here. First, frameworks should define components by operational role rather than by indicator category, specifying the criteria that determine whether a variable represents exposure, sensitivity, or capacity in a given application, rather than assigning named indicators to fixed components. The present review recorded nine indicators receiving more than one component assignment across studies, including road density, which functions as physical exposure in one tradition and as coping capacity in another; a framework organized by name cannot accommodate this, whereas one organized by role can. Second, frameworks should treat component membership as stage-dependent rather than fixed across the disaster cycle, since the same attribute may increase vulnerability during one phase and reduce it in another. Both guidelines are additions to the existing structures rather than replacements, and neither requires abandoning the exposure–sensitivity–capacity architecture on which current frameworks rest. However, due to the changeable nature of flood vulnerability over time and across space, these frameworks need to be updated and developed to use them as an efficient tool to quantify vulnerability to floods [96]. Finally, considering drivers and indicators as a constant expected effect in all vulnerability scenarios may affect outcomes because during some parts of an event, the same group may be vulnerable while not being vulnerable in others. In other words, the same indicator may have explanatory power at more than one event stage but with opposing implications for flood vulnerability. As an illustration, in terms of social vulnerability, children in segments of mitigation and preparedness, which are the two first phases of the disaster cycle, based on other indicators like education and family structure, can affect increasing or decreasing vulnerability [18,27,90,143,144].

This is an instance of a general property that may be termed stage-dependent vulnerability, and it applies across the demographic indicators most commonly used. Age illustrates it in both directions: children and older adults are more vulnerable before an event through limited awareness and reduced preparedness capacity, and during it through restricted mobility, yet in the recovery phase the elderly may hold accumulated assets, tenure security, and social ties that accelerate recovery relative to younger households. Gender illustrates it differently: men show elevated mortality during events through risk-taking and participation in rescue activity, while women face disproportionate burdens in the recovery phase through caregiving responsibilities, insecure tenure, and restricted access to compensation and credit.

The measurement consequence is direct. A single weight assigned to a demographic indicator represents an average across phases whose effects may carry opposing signs, so that an indicator with substantial phase-specific effects can receive a weight approaching zero, and a composite score can appear uninformative precisely where the underlying dynamics are strongest. This is a principal reason for the recommendation made above that component-level values be reported alongside composite indices, and it indicates that indicator weights are properly specified with respect to a defined phase of the disaster cycle rather than to the event as a whole.

The findings of this study reveal knowledge gaps regarding the development of flood vulnerability indicators. These findings are ordered based on the hierarchy of quantification of flood vulnerability applications in three sections: community, regional, and infrastructure vulnerability. Reduced vulnerability is mostly a result of literacy (especially in the

mitigation and preparedness phases of the flood disaster cycle). Along with literacy levels, having access to necessities like electricity, sanitation, drinking water systems, and low-interest bank loans for building dwellings helps to reduce social vulnerabilities [16,129]. In terms of demographic and health-related drivers, children and racial or ethnic minority groups appeared to be more vulnerable before the flood due to a lack of awareness and preparedness. Men and middle-aged people were more at risk during the flood because of their risk-taking behavior and participation in rescue and emergency activities [145,146]. Children and the elderly were also more at risk since they had trouble swimming and getting to safety. In addition, it was discovered that women, families with just one parent, and the elderly were particularly vulnerable due to resource limitations and challenges adjusting to disruptions in long-term care and services [27].

Findings from the review of regional-related studies illustrated that morphology, population density, urban population, human factors, and geology are the most influential indicators affecting flood vulnerability. These indicators directly influence land cover and other urban area density indicators such as floor area ratio, residential density, and building density. Land cover-related parameters, flood warning system, flood interaction culture, and slope are the second groups of most influential indicators affecting flood vulnerability [13,106,147]. Areas with a high proportion of vegetation cover reported less vulnerability to flood than built-up areas near downtowns. Consequently, to increase soil's ability to retain water and reduce impermeable areas, metropolitan areas and other urban areas should concentrate their efforts on land cover-related characteristics [148]. This can be accomplished by encouraging green development, such as building green roofs, promoting the use of porous pavement materials that allow water infiltration, raising the share of green space in new development projects, and increasing the density of green infrastructure [21,58,59].

The indicators characteristic of the two scales differ not only in content but in epistemic status, and this difference has consequences that composite indices tend to obscure. Regional indicators are predominantly physical: elevation, slope, soil classification, channel geometry, and land cover are stable over planning horizons, measurable by remote sensing without reference to administrative definitions, and largely independent of the observer. Community indicators are predominantly social: household composition, income, tenure, employment, and educational attainment change over short periods, are measurable only by survey or census, and depend on classification conventions that differ between jurisdictions and over time.

Three consequences follow. The two classes have different valid update intervals, so a composite combining them inherits the shorter, and an index whose physical layers remain current may nonetheless be obsolete in its social layers within a few years. They differ in transferability, since the relationship between slope and inundation holds across settings whereas the relationship between, say, tenure status and recovery capacity is mediated by institutions that do not. And they differ in what intervention can alter: physical attributes are largely fixed and are addressed through land-use control that determines what is placed where while social attributes respond to policy and are addressed through the capacities of those already present. A single composite score conflates constraints of these two kinds, which is a further reason for reporting component values separately.

In terms of infrastructures, more studies related to flood vulnerability have a case studies concept, and they quantified flood vulnerability in location- and hazard-specific as an application [149–151]. Many empirical flood-damage models are developed using limited, event- and location-specific damage datasets, which may restrict the range of flood-intensity and damage conditions represented, particularly observations of severe losses, and reduce model transferability across regions and flood types [152–157]. Water

depth is considered the essential factor to explain flood loss in most studies; however, other parameters such as flood duration, flow velocity, presence of debris, rate of rise, degree of severity, magnitude, and flood timing should be considered to quantify flood vulnerability comprehensively [158,159]. Although indicators like flood preparedness, the timing of the flood event, and flood alarms could help explain flood susceptibility, they currently only play a minor part in vulnerable models [12,29,147].

### 5.2. Flood Vulnerability Quantification: General Methods & Specific Methods

The ability to comprehensively assess the flood risk is essential to proactively avoid fatalities and financial losses, increase the resilience of communities and infrastructures to floods, and support decision-making for flood-related emergency management [160]. The findings of this study show that, as vulnerability quantification methods are more frequently included in the decision-making process, there is a need for a more thorough reflection on index construction. In addition, the decision-makers who want to utilize indexes must become more aware of their constraints (and potential). Using composite vulnerability indexes on one side and multiple flood vulnerability quantification methods on the other can lead to highly reliable results [161–163]. For instance, potential disaster loss (PDL) and potential economic development (PED) reveal the relationship between exposure and sensitivity. PDL means that the exposure development degree is higher than sensitivity, and there will be potential disaster losses. In contrast, PED means the situation will be helpful for the economic development of the locals. As well as potential defense defects and self-organized capability clarify the relationship between sensitivity and adaptive capacity. Finally, potential disaster frequency and potential resource waste for the relationship between exposure and adaptive capacity [12,16]. Therefore, the authors highly recommend that disaster practitioners use composite vulnerability indexes and multiple flood vulnerability quantification methods with particular attention to undertaking validation and sensitivity analysis to avoid the possible risks of inadequate allocation of resources [164].

The main concerns about specific methods are results validation because they have quantifiability limitations to using outdated prepared frameworks, selecting indicators from previous studies, and using one of the general methodologies that are location- and hazard-specific. For these reasons, using results from a few individual case studies to make comprehensive generalizations based on the dynamic concept of vulnerability may yield unreliable conclusions. However, these measurability limitations can be reduced by using different general methods to quantify vulnerability to floods, developing, mapping, analyzing quantitative indicators, and comparing the results to evaluate finding validation [17,18,114].

The opacity of these methods stands in tension with the transparency that regulatory decisions require, though the tension is unevenly distributed across the algorithms in use. Principal component analysis, the most frequently applied method in this corpus, is fully inspectable, since component loadings relate directly to the original indicators; tree-based methods yield variable-importance measures that identify which indicators drive a classification, if not how they interact. Neural networks and ensemble methods are genuinely opaque in the relevant sense, in that no accessible account can be given of why a particular unit received a particular classification.

This matters unevenly too. Opacity is of limited consequence where an output informs research or broad prioritization, but of considerable consequence where it carries regulatory effect for an identifiable parcel or household. Planning determinations are appealable, and a floodplain designation or development restriction that cannot be explained to the affected party cannot be defended before a planning authority or a court, irrespective of the model's

predictive accuracy. We therefore suggest that predictive machine-learning outputs are better suited to screening and prioritization, where they direct attention and resources, than to determinations requiring individual justification; and that where such methods do inform regulatory decisions, variable-importance measures or equivalent attribution should be reported alongside the classification, so that the basis of a determination remains auditable.

A direct comparison of accuracy between machine-learning and classical mathematical approaches cannot be drawn from the reviewed evidence, and this absence is informative. The two families are seldom applied to the same study area, they produce outputs of different kinds predicted class probabilities against composite scores and validation against observed flood outcomes is uncommon in studies of either type, so no common criterion exists on which to compare them. Claims that either family performs better are not supported by the corpus reviewed here.

The families can nonetheless be compared on dimensions the evidence does address. Data requirements differ most sharply: supervised machine-learning methods require observed outcome data for training, which is seldom available at the units at which vulnerability is assessed, whereas index-based methods require only indicator values and a weighting rule. Computational cost differs, though rarely decisively, since both are inexpensive at the spatial resolutions typical of this literature and neither is constrained by processing capacity. Interpretability favours the mathematical approaches, whose weights and aggregation rules are inspectable by construction. Transferability is limited for both, but for different reasons: index weights are calibrated to expert judgement or local covariance, while trained models encode the joint distribution of their training region.

The practical implication is that the choice between them is governed principally by data availability and by the use to which the output will be put, rather than by expected accuracy. Where labelled outcome data exist and the purpose is prediction or prioritization, machine-learning methods are appropriate; where such data are absent and the purpose is to represent an agreed conceptual structure transparently for regulatory use, index-based methods remain preferable. Establishing comparative accuracy would require studies applying both families to the same area and validating both against the same observed outcomes, which we identify as a research priority.

### *5.3. Flood Vulnerability Quantification: Challenges and Opportunities*

Although indicators are increasingly recognized as valuable tools for policy formulation and public communication, they are subject to quantifiability challenges. The use of social vulnerability indicators may lead to poor decision-making if cost, data accessibility, and measurability factors are given priority above validity [27]. As an example of measurability challenges, psychological sources of flood vulnerability are particularly difficult to quantify. Psychological drivers and their indicators, such as post-traumatic mental impacts, stress disorder, the process of getting back to normal life after the disaster, anxiety, and sleeping problems, might be difficult to quantify and need psychological sources because of high variation in process dynamics and the socio-economic background of the residents and communities affected [165–168].

Finally, addressing the myriad aspects of flood vulnerability necessitates considerably more in-depth viewpoints than broad categories like psychological sources of risk or lists of individual signs. Different outcomes and vulnerabilities may interact or make up for one another. For instance, not every member of stereotyped disadvantaged groups, such as the elderly or the less wealthy, faces the same challenges. Older adults may be more physically fragile yet have significant financial reserves to respond to a flood event, or underprivileged groups may have substantial social capital, which speeds up recovery [91,165].

Integration of qualitative and survey-based measurement with composite indices offers a practical route past this difficulty. Validated psychometric instruments exist for several of the constructs concerned, including post-traumatic stress, generalized anxiety, risk perception, and place attachment, and yield scaled scores that can be normalized and weighted on the same basis as the survey-derived socioeconomic indicators already common in community-scale assessment. The barrier is therefore procedural rather than conceptual: these constructs are measurable, but are seldom measured in flood-vulnerability studies.

Three conditions apply. Instruments should be validated rather than constructed ad hoc for a single study, since the credibility of a psychological indicator rests on the measurement properties of the instrument producing it. Psychological indicators should be reported as a distinct component rather than absorbed into social sensitivity, because they change over shorter intervals than demographic indicators and are strongly stage-dependent, an attribute discussed above. And sampling should be designed for the spatial unit at which the index is constructed, since psychometric measurement is conducted at individual or household level and does not aggregate straightforwardly to district or municipal scores without explicit assumptions about within-unit distribution. Mixed-methods designs combining structured psychometric survey with qualitative interview material are well suited to this, the qualitative component serving to establish whether an instrument developed in one cultural setting retains its meaning in another.

A conditional failure probability can be expressed as an expected duration of service disruption for a given event magnitude, which corresponds directly to the continuity-of-service obligations that utilities and transport authorities already hold. It can be expressed as an expected annual loss by integrating failure probability against the exceedance probability of the loading, yielding a monetary quantity commensurable with the capital and maintenance budgets against which investment decisions are actually made. Or it can be expressed as the loading at which failure probability exceeds a stated threshold, which maps onto the design return periods already embedded in floodplain regulation and building codes. Each preserves the underlying analysis and changes only the quantity reported, and each converts an output that municipal decision-makers cannot readily use into one that corresponds to an existing decision instrument. We suggest that infrastructure-scale assessments intended to inform planning report at least one such derived quantity alongside the fragility or reliability results themselves.

Low transferability recurred across the reviewed corpus and was attributable to three distinguishable sources rather than to a single cause. The first and most pervasive is calibration dependence. Indicator weights are typically derived either from local expert panels through the analytic hierarchy process and its fuzzy variants, or from principal component analysis of a single regional dataset, so the resulting weight structure expresses the judgements and covariance of one setting and carries no demonstrated validity beyond it. Applying such weights elsewhere transfers an untested assumption rather than an established relationship. The second is data-system dependence. The indicators that can be operationalized in any given study are bounded by the national census, cadastral, and administrative reporting systems that supply them, and these differ across jurisdictions in the variables collected, the spatial units at which they are reported, and the frequency with which they are updated. An index constructed from one country's census cannot generally be reconstructed from another's, and partial reconstruction with substituted proxies changes the construct being measured. The third, which operates principally at the infrastructure scale, is built-environment dependence.

Empirical damage functions and fragility curves encode the construction typologies, structural materials, foundation and ground-floor configurations, building codes, and

drainage design standards of the settings in which they were derived, so their applicability is bounded by the physical similarity of the receiving stock rather than by data availability alone. These three sources are not equally binding across scales: at the community and regional scales, data-system dependence and calibration dependence are the dominant constraints, whereas at the infrastructure scale the physical characteristics of the exposed stock dominate. This distinction matters for practice, because the remedies differ. Calibration dependence is addressed by testing weighting schemes against observed flood outcomes in more than one setting; data-system dependence is addressed by reporting operational definitions and units in sufficient detail that equivalent proxies can be identified; and built-environment dependence is addressed by reporting the construction and design characteristics of the calibration sample, so that receiving users can judge similarity before transfer rather than after.

The reviewed studies frequently included impervious surface area, building density, vegetation cover, floor area ratio, and related land-use variables in exposure or sensitivity assessments. These recurring indicators suggest that zoning, development controls, stormwater requirements, green infrastructure, and nature-based solutions are relevant planning levers. However, their relative effectiveness should be established through local calibration and validation against observed flood impacts rather than inferred from indicator frequency alone.

The instruments through which this can be achieved are already available to planning authorities, and each corresponds to an indicator in the inventory presented in Appendix A. Green-infrastructure density is regulated through maximum impervious-surface ratios in zoning provisions, minimum green-space and tree-canopy requirements attached to development approval, on-site stormwater retention and detention standards, and permeable-surface specifications in subdivision and parking regulation. Building codes govern the complementary attributes at the structure scale, including ground-floor configuration, basement provision, freeboard, and flood-resistant materials, which appear among the physical sensitivity indicators identified in this review. Each of these converts a measured vulnerability indicator into an enforceable development standard, and because the indicators are measurable from existing municipal GIS and remote-sensing data, the effect of the standard can be monitored rather than assumed.

Rural settings require different instruments, since development control is generally weaker and land cover is determined principally through agricultural land management rather than through development approval. The operative levers there are riparian buffer and setback requirements, restrictions on cultivation and drainage in floodplains, and conditionality attached to agricultural support payments, together with catchment-scale measures including floodplain reconnection and managed retention on agricultural land. These instruments act on the same indicators (land cover, impervious surface, and distance to watercourse) through a different regulatory route, and their effectiveness should be established through local calibration rather than inferred from indicator frequency alone.

Planning agencies seeking to apply the indicators synthesized in this review should prioritize those with the strongest documented links to land-cover change, impervious surface coverage, green infrastructure density, and building density in particular, when designing zoning ordinances, floodplain overlay districts, or stormwater management requirements, since these indicators are both measurable with existing GIS and remote-sensing data and directly responsive to land-use policy interventions. At the same time, the indicator-interaction gap identified above means planners should treat any single composite vulnerability score with caution: a parcel or district with a favorable aggregate score may still contain specific, actionable land-use risks that the composite obscures, underscoring

the value of disaggregated, component-level reporting (exposure, sensitivity, adaptive capacity, coping capacity) over single-number indices in planning decision support.

#### 5.4. Implications for Practice

For local governments and planning agencies, the indicator framework synthesized in this review (Appendix A) offers a basis for incorporating standardized flood vulnerability metrics into comprehensive plans and floodplain management ordinances, rather than relying solely on FEMA flood-zone designations, which capture exposure but not sensitivity or adaptive capacity [168]. For infrastructure agencies, the infrastructure-specific quantification methods reviewed in the Infrastructure-Based Vulnerability Quantification subsection above (e.g., fragility-curve and Bayesian network approaches) provide a basis for prioritizing capital improvement and maintenance spending toward the infrastructure assets with the highest predicted vulnerability, rather than spreading limited resilience budgets evenly across a system. For emergency managers, the demographic vulnerability findings discussed above, particularly the elevated vulnerability of children, the elderly, and single-parent households during specific phases of the disaster cycle, support targeting evacuation planning, public communication, and post-flood recovery resources toward these groups at the specific disaster-cycle phases where they are shown to be most at risk, rather than applying uniform outreach across the general population. For community resilience planners, the consistent finding that vegetation cover and green infrastructure density reduce vulnerability [61,62] supports prioritizing nature-based solutions in resilience funding allocations alongside traditional gray infrastructure.

#### 5.5. Limitations

This review has six principal limitations. First, the search was restricted to Scopus and English-language peer-reviewed journal articles, which may have excluded relevant studies indexed elsewhere or reported in other languages and gray literature. The document-type restriction does not fall evenly across the three application scales. In infrastructure engineering, conference proceedings, agency technical reports, standards documentation, and software manuals carry a substantially larger share of the primary evidence than they do in the community and regional literatures, and fragility functions, depth–damage models, and network-performance analyses are frequently first reported through these channels. The restriction therefore under-samples infrastructure-scale evidence specifically, and it compounds the single-database restriction, since the sources indexing this material most comprehensively were also not searched.

The smaller infrastructure-scale representation reported in Section 4.1 should accordingly be interpreted as a feature of the review’s sampling frame rather than as a measure of research activity at that scale. Peer-reviewed journal publication was retained as an eligibility condition because consistent peer review and reporting requirements were necessary for comparability across a methodologically heterogeneous corpus, but this was a trade-off rather than a cost-free choice. Second, disciplinary differences in terminology and search syntax may have reduced retrieval of studies framed as susceptibility, damage, fragility, disruption, or resilience rather than vulnerability. The methods block likewise did not include “artificial intelligence,” “deep learning,” or “neural network,” and although the broader terms in that block make non-retrieval on this ground unlikely, it cannot be excluded.

Third, substantial heterogeneity in constructs, scales, data sources, outcomes, and validation procedures prevented meta-analysis and limited direct comparison. Fourth, indicator harmonization required reviewer judgment, although consolidation and classification decisions were independently reviewed. Fifth, most included studies were context-specific case studies, and the tailored methodological appraisal used in this review is not a validated

risk-of-bias instrument. The taxonomy and indicator inventory should therefore support context-sensitive method selection and local calibration rather than universal application.

Sixth, the methodological appraisal of the included studies is reported in aggregate rather than study by study. The characteristics of each included study—citation, geographic setting, study type, application scale, and principal method family—are reported individually in Appendix A, Table A5, but the eleven-domain appraisal scores are summarized across the corpus rather than presented per study, because domain scores were used descriptively and were not applied to include, exclude, or weight studies.

The review identifies independent validation against observed flood outcomes as uncommon across the corpus; publication bias implies that this understates rather than overstates the difficulty, since studies that attempted validation and obtained weak agreement are among those least likely to have been published. Null and inconclusive results are of particular value in this field, because a weighting scheme that performs no better than equal weighting, or an index that fails to distinguish areas that flooded from those that did not, is directly informative for method selection. We encourage journals and reviewers to treat such findings as publishable contributions.

## 6. Conclusions

This systematic review consolidated 26 years of literature (2000–2025) on the quantification of flood vulnerability for communities, regions, and infrastructure, synthesizing 144 studies conducted and reported in accordance with PRISMA 2020.

Against the first objective, the review catalogued the indicators and methods in use, yielding 217 unique harmonized indicators represented by 226 indicator–component assignments across exposure, sensitivity, adaptive capacity, and coping capacity (Appendix A), together with a taxonomy of seven method families and their analytical platforms. Against the second, it integrated three application scales normally studied in isolation into a single framework relating constructs, indicators, methods, and outcomes, showing that the corpus converges on a common procedural architecture and diverges principally at the weighting and aggregation stages. Against the third, it identified four methodological gaps: inconsistent construct definitions, limited independent validation, minimal treatment of indicator interaction, and low transferability arising from locally calibrated weights, data-system dependence, and built-environment specificity.

Three findings carry particular significance. Land-cover and land-use variables emerged repeatedly as central drivers of exposure and sensitivity at every scale, making land-use planning a uniquely cross-cutting and actionable lever; this warrants formalization through territorial planning instruments at local and departmental levels, since impervious-surface limits, green-space requirements, and floodplain overlays convert measured indicators directly into enforceable standards. Second, the predominance of case studies, 106 of 144, means most metrics remain validated only where they were developed. The calibrations most urgently needed are those spanning the widest contextual gaps: tropical and monsoonal basins against temperate ones, rapidly urbanizing settlements against established municipalities, and rural and agricultural settings against dense metropolitan ones—the more so because projected increases in flood loss are concentrated in regions least represented in this corpus. Third, indicator interactions cut across components: exposure and sensitivity are not independent, since the same settlement density that places people in harm's way also shapes their capacity to respond, and the same attribute may increase vulnerability at one stage of an event and decrease it at another. Composite scores that assign a single static weight to a demographic indicator therefore risk mathematically over-representing it while concealing the dynamics that matter for intervention, which is why component-level reporting should accompany any composite index.

The inventory in Appendix A is intended for use, not only for reference. A municipality reviewing development in a flood-prone district can select measurable physical-sensitivity indicators (impervious surface, green-infrastructure density, ground-floor typology, distance from watercourses), screen them against its existing GIS and cadastral holdings, and apply them to identify which parcels concentrate risk before permissions are granted rather than after losses occur. Applied at that stage, the difference is measured in buildings not placed in harm's way.

Two priorities follow for research. Standardized approaches to indicator weighting and validation should be developed and tested across contexts, and interactions among exposure, sensitivity, and adaptive capacity should be modelled explicitly rather than assumed away. To both we add a third: intensifying climate variability means methods calibrated solely on historical records will describe a hazard regime that no longer obtains, and vulnerability assessment must become forward-looking, incorporating projected land-use and climate trajectories rather than extrapolating from the observed past. Progress on all three depends on evidence that can be independently examined, and we therefore urge journals and funding bodies to require publication of the underlying indicator datasets, weighting matrices, and validation results in vulnerability research, and to treat null and inconclusive findings as publishable contributions.

Standardization of this kind should not be mistaken for uniformity. The evidence assembled here shows that indicator relevance, weight, and availability are properly determined by context; what requires standardizing is how methods are reported, not which methods are used. The objective is comparability without homogenization, so that a coastal megacity and a rural floodplain community can each be assessed appropriately and their results still be read together.

The most consequential advances in this field will come from the genuine intersection of social science, sustainable development, and civil engineering, rather than from refinement within any one of them. The measurement traditions synthesized here (composite social indices, geospatial multicriteria analysis, and performance-based engineering) remain largely incommensurable and bridging them is the principal opportunity now open to flood vulnerability science [169–172].

For those directing planning departments, one step can be taken immediately: audit the indicators currently underlying your flood-risk designations against the inventory in Appendix A, identify which components (exposure, sensitivity, adaptive capacity, coping capacity) your existing assessment omits, and require that the next revision of your floodplain and zoning provisions report them separately rather than as a single score. Most jurisdictions will find they measure exposure well and capacity barely at all. That gap is where avoidable losses accumulate, and closing it requires no new data collection, only the decision to look.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su182010375/s1>, Table S1: PRISMA 2020 Checklist.

**Author Contributions:** Conceptualization, M.M. and M.T.; methodology, M.M. and M.T.; investigation, M.M. and S.R.; data curation, M.M. and S.R.; writing—original draft preparation, M.M., F.N. and S.R.; writing—review and editing, M.T., F.N. and S.R.; visualization, M.M. and S.R.; supervision, M.T. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Institutional Review Board Statement:** Not Applicable

**Informed Consent Statement:** Not Applicable

**Data Availability Statement:** The harmonized indicator inventory supporting this review is reported in full in Appendix A, Tables A1–A4, comprising 217 unique harmonized indicators and their 226 component assignments across exposure, sensitivity, adaptive capacity, and coping capacity. The completed PRISMA 2020 checklist is provided in Table S1. The study-level extraction database and the indicator coding dictionary, which records the original indicator term as reported in each source study, the harmonized label, the operational definition, the unit of measurement, the assigned vulnerability component, the source study, and the reason for consolidation or separation, are available from the corresponding author upon request.

**Conflicts of Interest:** Author M.M. is employed by Schnabel Engineering LLC. The company had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results. The authors declare no other conflicts of interest. The authors declare no conflicts of interest.

## Abbreviations

| Abbreviation | Definition                                           |
|--------------|------------------------------------------------------|
| AHC          | Agglomerative Hierarchical Clustering                |
| AHP          | Analytic Hierarchy Process                           |
| ANN          | Artificial Neural Network                            |
| ANP          | Analytic Network Process                             |
| BBN          | Bayesian Belief Network                              |
| CDDM         | Coordinated Development Degree Model                 |
| CCR-DEA      | Charnes–Cooper–Rhodes Data Envelopment Analysis      |
| CityGML      | City Geography Markup Language                       |
| DEM          | Digital Elevation Model                              |
| DOI          | Digital Object Identifier                            |
| DT           | Decision Tree                                        |
| ELECTRE      | Élimination et Choix Traduisant la Réalité           |
| EM-DAT       | Emergency Events Database                            |
| ESDAC        | European Soil Data Centre                            |
| FAHP         | Fuzzy Analytic Hierarchy Process                     |
| FCEM         | Fuzzy Comprehensive Evaluation Method                |
| FEMA         | Federal Emergency Management Agency                  |
| FS           | Flood Susceptibility                                 |
| FVR          | Flood Vulnerability Rate                             |
| GDP          | Gross Domestic Product                               |
| GIS          | Geographic Information System                        |
| GT           | Game Theory                                          |
| HAZUS        | Hazards U.S.                                         |
| HAZUS-MH     | Hazards U.S. Multi-Hazard                            |
| HEC-FDA      | Hydrologic Engineering Center Flood Damage Analysis  |
| HEC-RAS      | Hydrologic Engineering Center River Analysis System  |
| IDF          | Intensity–Duration–Frequency                         |
| IIASA        | International Institute for Applied Systems Analysis |
| IPCC         | Intergovernmental Panel on Climate Change            |
| ISEVI        | Integrated Socio-Economic Vulnerability Index        |
| KNN          | k-Nearest Neighbors                                  |
| LCCA         | Latent Class Cluster Analysis                        |
| LVI          | Livelihood Vulnerability Index                       |
| MAC          | Main Workers in Agriculture and Cultivation          |
| MATLAB       | Matrix Laboratory                                    |
| MCDA         | Multicriteria Decision Analysis                      |
| MFCSVI       | Multi-Faceted Composite Social Vulnerability Index   |
| MIVES        | Integrated Value Model for Sustainability Assessment |

|           |                                                                                                         |
|-----------|---------------------------------------------------------------------------------------------------------|
| ML        | Machine Learning                                                                                        |
| NCAR      | National Center for Atmospheric Research                                                                |
| NDVI      | Normalized Difference Vegetation Index                                                                  |
| OLS       | Ordinary Least Squares                                                                                  |
| PCA       | Principal Component Analysis                                                                            |
| PROMETHEE | Preference Ranking Organization Method for Enrichment Evaluations                                       |
| QGIS      | Open-source Geographic Information System software                                                      |
| RF        | Random Forest                                                                                           |
| RIFVG     | Regional Integrated Flood-Vulnerability Grade                                                           |
| RISEVI    | Regional Integrated Socio-Economic Vulnerability Index                                                  |
| RVS       | Relative Vulnerability Score                                                                            |
| SEI       | Socio-Economic Index                                                                                    |
| SETS      | Social–Ecological–Technological Systems                                                                 |
| SEV       | Socio-Economic Vulnerability                                                                            |
| SPN       | Stochastic Petri Net                                                                                    |
| SPSS      | Statistical Package for the Social Sciences                                                             |
| SU        | Spatial Unit                                                                                            |
| SWMM      | Storm Water Management Model                                                                            |
| TAN       | Tree-Augmented Naive Bayes                                                                              |
| TFN       | Triangular Fuzzy Number                                                                                 |
| TFN-AHP   | Triangular Fuzzy Number–Analytic Hierarchy Process                                                      |
| TOPSIS    | Technique for Order Preference by Similarity to Ideal Solution                                          |
| UNDRR     | United Nations Office for Disaster Risk Reduction                                                       |
| USACE     | U.S. Army Corps of Engineers                                                                            |
| VIKOR     | VlseKriterijumska Optimizacija I Kompromisno Resenje—Multicriteria Optimization and Compromise Solution |

## Appendix A

The completed PRISMA 2020 checklist for this review is provided in Supplementary Table S1.

**Table A1.** Exposure vulnerability indicators.

| Criteria        | Indicator                                                                          |
|-----------------|------------------------------------------------------------------------------------|
| Social Exposure | Total population                                                                   |
|                 | Health centers                                                                     |
|                 | Hospital beds                                                                      |
|                 | Medical staff                                                                      |
|                 | Kindergartens                                                                      |
|                 | Elementary schools                                                                 |
|                 | Secondary schools                                                                  |
|                 | Retirement homes                                                                   |
|                 | Tourist accommodation                                                              |
|                 | Population per settlement area                                                     |
|                 | Vacant households                                                                  |
|                 | Underground built-up area                                                          |
|                 | Permanent households                                                               |
|                 | Households with 1 story above ground level and/or another story below ground level |

Table A1. Cont.

| Criteria          | Indicator                                                                                                |
|-------------------|----------------------------------------------------------------------------------------------------------|
| Social Exposure   | Households with 2 or more stories above ground level                                                     |
|                   | Foreigners                                                                                               |
|                   | New residents                                                                                            |
|                   | Height Distribution                                                                                      |
|                   | Riverside Evacuation                                                                                     |
|                   | Training of Citizens                                                                                     |
|                   | Tourism                                                                                                  |
|                   | Number of female members                                                                                 |
|                   | English proficiency                                                                                      |
|                   | Household head's education level                                                                         |
|                   | Total members/family size                                                                                |
|                   | Female-headed households                                                                                 |
| Economic Exposure | Number of dwellings located at flood-prone areas                                                         |
|                   | Length of the streets (meters) located at flood-prone areas                                              |
|                   | Electrical transformers located at flood-prone areas                                                     |
|                   | Parks and gardens (m <sup>2</sup> ) located at flood-prone areas                                         |
|                   | Education infrastructures (kindergartens, elementary and secondary schools) located at flood-prone areas |
|                   | Retirement homes located at flood-prone areas                                                            |
|                   | Bridges located at flood-prone areas                                                                     |
|                   | Protections of riverbanks (linear meters) located at flood-prone areas                                   |
|                   | Secondary houses                                                                                         |
|                   | Dwellings with 1 story above ground level                                                                |
|                   | Dwellings with 1 or more stories below ground level                                                      |
|                   | dependent solely on agriculture as a source of income                                                    |
| Physical Exposure | Total resident population                                                                                |
|                   | Local gross domestic product                                                                             |
|                   | Classification                                                                                           |
|                   | Urban Detailed Plan                                                                                      |
|                   | Hydrometric                                                                                              |
|                   | Meteorology                                                                                              |
|                   | Wall Condition                                                                                           |
|                   | Fall Barrier                                                                                             |
|                   | Surveillance                                                                                             |
|                   | Flow velocity                                                                                            |
|                   | water depth                                                                                              |
|                   | Flooded area                                                                                             |
|                   | Neighborhoods affected                                                                                   |
|                   | Critical infrastructure (CI)                                                                             |

**Table A1.** *Cont.*

| Criteria            | Indicator                                                                                      |
|---------------------|------------------------------------------------------------------------------------------------|
| Physical Exposure   | River Distance                                                                                 |
|                     | Land use                                                                                       |
|                     | Encroachment to River Buffer                                                                   |
|                     | Bridges Distance                                                                               |
|                     | Soil Classification                                                                            |
|                     | Sinuosity                                                                                      |
|                     | Channel Width                                                                                  |
|                     | Channel Characteristics                                                                        |
|                     | River Bed Slope                                                                                |
|                     | Aspect                                                                                         |
|                     | Elevation                                                                                      |
|                     | Precipitation                                                                                  |
|                     | Temperature                                                                                    |
|                     | Evaporation                                                                                    |
|                     | Runoff                                                                                         |
|                     | Bridge Conditions                                                                              |
|                     | Road density                                                                                   |
| Ecological Exposure | Proximity of ecosystem (park, floodplain) to Toxic Release Inventory (TRI) and Superfund sites |
|                     | Combination of shape index and average patch size                                              |
| Health Exposure     | Dependency ratio                                                                               |
|                     | Average distance to nearest health facility                                                    |
|                     | Number of ill/disabled members                                                                 |
|                     | Households that reported diseases after floods                                                 |
|                     | Inundated well (use for drinking water)                                                        |
|                     | Social security affiliation                                                                    |

**Table A2.** Sensitivity vulnerability indicators.

| Criteria           | Indicator                                       |
|--------------------|-------------------------------------------------|
| Social Sensitivity | Inhabitants aged 0–4                            |
|                    | Inhabitants aged 5–14                           |
|                    | Population projection aged 0–4 for 2025         |
|                    | Population projection aged 5–14 for 2025        |
|                    | Unemployment rates                              |
|                    | Long-term unemployed people                     |
|                    | Households where any unemployed people live     |
|                    | Inhabitants aged 65 or older                    |
|                    | Population projection aged 65 or older for 2025 |
|                    | Dependency rates: males                         |

Table A2. Cont.

| Criteria             | Indicator                                                                        |
|----------------------|----------------------------------------------------------------------------------|
|                      | Dependency rates: females                                                        |
|                      | Households where people aged 65 or older live                                    |
|                      | Illiterate people                                                                |
|                      | Distance to the nearest hospital                                                 |
|                      | Travel time to the nearest hospital                                              |
|                      | Distance to the nearest health center                                            |
|                      | Travel time to the nearest health center                                         |
|                      | Female population                                                                |
|                      | Children population                                                              |
|                      | state of conservation                                                            |
|                      | Poverty level                                                                    |
|                      | Literacy rate                                                                    |
|                      | Attitude                                                                         |
|                      | Decentralization                                                                 |
|                      | Community participation                                                          |
|                      | Households that reported no member in school                                     |
|                      | Old population                                                                   |
|                      | Number of workers in agricultural sector                                         |
|                      | Number of workers in industry, construction and services sectors                 |
|                      | Tourist accommodation capacity                                                   |
| Economic Sensitivity | Unemployment rate                                                                |
|                      | Municipal debt per inhabitant (\$/inhab)                                         |
|                      | Replacement costs (\$/m <sup>2</sup> ) of dwellings located at flood-prone areas |
|                      | Mean age of the vehicle fleet                                                    |
|                      | Vehicle fleet                                                                    |
|                      | Households in good condition                                                     |
|                      | dependent solely on agriculture as a source of income                            |
|                      | Average Agricultural Livelihood Diversification Index                            |
|                      | Rural fixed asset investment/Town population                                     |
|                      | Local resource base                                                              |
|                      | Diversification                                                                  |
|                      | Stability                                                                        |
|                      | Accessibility                                                                    |
|                      | Unemployed head                                                                  |
|                      | Other economic activities                                                        |
|                      | Households' monthly income                                                       |
|                      | Households with no assets                                                        |
|                      | Households that do not receive financial support                                 |
|                      | Dependency ratio                                                                 |

Table A2. Cont.

| Criteria                 | Indicator                                                                       |
|--------------------------|---------------------------------------------------------------------------------|
| Physical Sensitivity     | Building quality condition                                                      |
|                          | Building age                                                                    |
|                          | Impervious surface                                                              |
|                          | Green Infrastructure density                                                    |
|                          | Existence of water damage                                                       |
|                          | Ground floor typology                                                           |
|                          | Existence of a basement                                                         |
|                          | Openings ground floor                                                           |
|                          | Roof type                                                                       |
|                          | Structural material                                                             |
|                          | Distance from rivers                                                            |
|                          | Flood duration                                                                  |
|                          | Inundation depth of households                                                  |
|                          | Households built with clay/huts/tents                                           |
|                          | Households that use firewood as cooking fuel/s                                  |
|                          | Households that experience frequent floods                                      |
|                          | Damage from previous floods                                                     |
|                          | Households that do not have alternative access during floods                    |
|                          | Households located in areas without tarred roads or served only by gravel roads |
| Agricultural Sensitivity | Facade material                                                                 |
|                          | Area of major crops/Town area                                                   |
|                          | Vegetable yield/Town area                                                       |
|                          | Grain output/Town area                                                          |
| Ecological Sensitivity   | % bare soil within the area                                                     |
|                          | % wetland within the area                                                       |
|                          | Degraded land                                                                   |
|                          | Overused land                                                                   |
|                          | Area under forest                                                               |

Table A3. Adaptive Capacity vulnerability indicators.

| Criteria                 | Indicator                                                                                                    |
|--------------------------|--------------------------------------------------------------------------------------------------------------|
| Social Adaptive Capacity | Age of the household head                                                                                    |
|                          | Gender of the household head                                                                                 |
|                          | Education of the household head                                                                              |
|                          | View of nature and environmental                                                                             |
|                          | Previous actions individual and collectively due to hazards and disasters                                    |
|                          | Number of stakeholders involved in hazard/disaster issues according to disaster cycle: before, during, after |

Table A3. Cont.

| Criteria                                       | Indicator                                                                 |
|------------------------------------------------|---------------------------------------------------------------------------|
| Social Adaptive Capacity                       | Renter (% people who are renters)                                         |
|                                                | Standard deviation of slope                                               |
|                                                | Cultural value                                                            |
|                                                | school curricula                                                          |
|                                                | Emergency response drills                                                 |
| Economic Adaptive Capacity                     | Total Monthly Income of the household                                     |
|                                                | Land Holding Size of the household                                        |
|                                                | Agricultural Source of Income of the household head                       |
|                                                | Non-Agricultural Source of Income of the household head                   |
|                                                | Household Size                                                            |
|                                                | Percent of households with family member working in a different community |
|                                                | Number of hospitals                                                       |
|                                                | Number of churches                                                        |
|                                                | Number of schools                                                         |
|                                                | socio-economic status                                                     |
|                                                | Insurance market                                                          |
|                                                | Mitigation loans                                                          |
|                                                | Public works                                                              |
|                                                | Farmers' net income                                                       |
|                                                | Township financial income                                                 |
|                                                | Reconstruction loans                                                      |
| Early-warning Adaptive Capacity                | Rainfall warning station density                                          |
|                                                | Public awareness programs                                                 |
|                                                | previous intervention                                                     |
| Ecological Adaptive Capacity                   | Productivity (+) based on Normalized Difference Vegetation Index (NDVI)   |
|                                                | Building area (% building area within the area)                           |
| Physical Adaptive Capacity                     | Emergency centers                                                         |
|                                                | Number of dwellings                                                       |
|                                                | Drainage system                                                           |
|                                                | Preventive structures                                                     |
|                                                | Environmental management                                                  |
| Management and institutional Adaptive Capacity | Risk management committee                                                 |
|                                                | Risk map                                                                  |
|                                                | Emergency plan                                                            |
|                                                | Institutional capacity building                                           |
|                                                | Communication                                                             |
|                                                | Network degree density                                                    |
|                                                | Trusting others                                                           |
|                                                | Average number of friends in their associations reported                  |

**Table A4.** Coping Capacity vulnerability indicators.

| Criteria                 | Indicator                                      |
|--------------------------|------------------------------------------------|
| Social Coping Capacity   | Households in good condition                   |
|                          | Households in poor condition                   |
|                          | Inhabitants aged 15–64                         |
|                          | Road density                                   |
|                          | Shelter density                                |
|                          | Hospital density                               |
|                          | Training of Citizens                           |
|                          | GDP per capita                                 |
|                          | Public participation                           |
|                          | Local risk management groups                   |
|                          | Population projection aged 15–64 for 2025      |
|                          | Municipal available budget per capita          |
|                          | Tax base of the property tax (thousands of \$) |
|                          | Per capita income (\$/inhab.)                  |
|                          | Main houses                                    |
|                          | Fixed investments per inhabitant (\$/inhab.)   |
|                          | Local emergency funds                          |
|                          | Access to local emergency funds                |
|                          | Access to international emergency funds        |
|                          | Municipal budget per inhabitant (\$/inhab.)    |
| Physical Coping Capacity | Classification                                 |
|                          | Urban Detailed Plan                            |
|                          | Hydrometric                                    |
|                          | Meteorology                                    |
|                          | Land use planning                              |
|                          | Building codes                                 |
|                          | Retrofitting/maintenance                       |

**Table A5.** Complete list and principal characteristics of the 144 included studies. Application-scale categories are not mutually exclusive; a study addressing more than one unit or system is listed under every applicable scale. Method families are likewise non-exclusive, and the column reports the principal family only.

| No. | Author(s), Year                  | Country/Region | Study Type | Application Scale | Principal Method Family                    |
|-----|----------------------------------|----------------|------------|-------------------|--------------------------------------------|
| 1   | Abebe et al. (2018) [21]         | Canada         | Case study | Regional; urban   | Machine learning (Bayesian belief network) |
| 2   | Alabbad & Demir (2022) [117]     | USA (Iowa)     | Case study | Community         | Composite index                            |
| 3   | Aroca-Jiménez et al. (2020) [73] | Spain          | Case study | Regional          | Composite index; MCDA; statistical         |

Table A5. Cont.

| No. | Author(s), Year                     | Country/Region                | Study Type        | Application Scale   | Principal Method Family                 |
|-----|-------------------------------------|-------------------------------|-------------------|---------------------|-----------------------------------------|
| 4   | Aslam et al. (2024) [145]           | Pakistan (Khyber Pakhtunkhwa) | Case study        | Community           | Composite index                         |
| 5   | Avand & Moradi (2022) [126]         | Iran                          | Case study        | Community; regional | Machine learning; statistical           |
| 6   | Babcicky et al. (2021) [165]        | Austria                       | General/technical | Community           | Statistical                             |
| 7   | Balakrishnan et al. (2020) [42]     | USA (Houston)                 | Case study        | Infrastructure      | Network performance                     |
| 8   | Besarra et al. (2025) [158]         | Philippines (Leyte)           | Case study        | Infrastructure      | Fragility and vulnerability functions   |
| 9   | Bhattacharjee & Behera (2018) [96]  | India (West Bengal)           | Case study        | Community           | Composite index (LVI)                   |
| 10  | Bucherie et al. (2022) [16]         | Ecuador                       | Case study        | Community; regional | Statistical (PCA); expert knowledge     |
| 11  | Chacowry et al. (2018) [90]         | Mauritius                     | Case study        | Community           | Qualitative-supported index             |
| 12  | Chakraborty et al. (2020) [91]      | Canada                        | Case study        | Community           | Composite index; statistical            |
| 13  | Chang et al. (2021) [111]           | USA (six cities)              | Case study        | Regional            | Composite index (SETS)                  |
| 14  | Chang et al. (2025) [2]             | Pakistan                      | Case study        | Regional            | Composite index; MCDA                   |
| 15  | Chia et al. (2020) [148]            | Hong Kong SAR                 | Case study        | Regional; urban     | Composite index                         |
| 16  | Chuang et al. (2020) [92]           | Taiwan (New Taipei)           | Review            | Community; regional | Composite index                         |
| 17  | Cimellaro et al. (2019) [49]        | USA (New York)                | Case study        | Infrastructure      | Network performance; interdependency    |
| 18  | Daneshifar & Kashani (2024) [118]   | Iran                          | General/technical | Infrastructure      | Probabilistic; reliability              |
| 19  | de Andrade & Szlafsztein (2018) [9] | Brazil (Amazon)               | Case study        | Community; regional | Composite index                         |
| 20  | de Brito et al. (2017) [93]         | Brazil (Taquari-Antas)        | Case study        | Regional            | MCDA (Delphi)                           |
| 21  | Deroliya et al. (2022) [18]         | India                         | Case study        | Regional            | Machine learning; CCR-DEA               |
| 22  | Diakakis et al. (2020) [39]         | Greece (Mandra)               | Case study        | Infrastructure      | Empirical damage assessment             |
| 23  | Duan et al. (2022) [10]             | Global                        | General/technical | Regional            | MCDA (game theory; TFN-AHP)             |
| 24  | Dutta et al. (2013) [152]           | Australia; Japan              | Case study        | Infrastructure      | Damage and loss modelling               |
| 25  | Działek et al. (2016) [141]         | Poland                        | Case study        | Community           | Statistical                             |
| 26  | Eini et al. (2020) [17]             | Iran                          | Case study        | Regional; urban     | MCDA (fuzzy AHP); machine learning      |
| 27  | Esraz-UI-Zannat et al. (2024) [58]  | Australia                     | Review            | Regional; urban     | Composite index                         |
| 28  | Figueiredo et al. (2021) [159]      | Portugal                      | General/technical | Infrastructure      | Component-based vulnerability modelling |

Table A5. Cont.

| No. | Author(s), Year                        | Country/Region     | Study Type        | Application Scale         | Principal Method Family                |
|-----|----------------------------------------|--------------------|-------------------|---------------------------|----------------------------------------|
| 29  | Frick-Trzebitzky et al. (2017) [52]    | Ghana (Accra)      | Case study        | Community                 | Qualitative-supported index            |
| 30  | Gandini et al. (2020) [114]            | Spain              | Case study        | Infrastructure; urban     | MCDA (MIVES; AHP)                      |
| 31  | Ganji et al. (2022) [13]               | Iran (Aq'Qala)     | Case study        | Regional                  | MCDA (AHP; TFN-AHP)                    |
| 32  | Grahn & Nyberg (2017) [105]            | Sweden             | Case study        | Regional                  | Composite index; geospatial            |
| 33  | Hahn et al. (2009) [95]                | Mozambique         | Case study        | Community                 | Composite index (LVI; LVI-IPCC)        |
| 34  | Hamidi et al. (2025) [32]              | United Kingdom     | Review            | Community                 | Composite index                        |
| 35  | Hanna et al. (2025) [98]               | New Zealand        | Case study        | Regional                  | Policy and land-use analysis           |
| 36  | Hardmeyer & Spencer (2007) [135]       | USA (Rhode Island) | Case study        | Regional                  | Composite index; geospatial            |
| 37  | Hieronimi et al. (2023) [166]          | Germany            | Case study        | Community                 | Qualitative-supported index            |
| 38  | Hosseinzadehtalaei et al. (2020) [106] | Europe             | General/technical | Regional                  | Composite index; satellite data-driven |
| 39  | Hu et al. (2017) [100]                 | China (Beijing)    | Case study        | Regional                  | Composite index; geospatial            |
| 40  | Ingle & Chattopadhyay (2022) [116]     | India (Nagpur)     | Case study        | Community                 | Composite index                        |
| 41  | Jha & Gundimeda (2019) [161]           | India (Bihar)      | Case study        | Regional                  | Composite index                        |
| 42  | Karunarathne & Lee (2020) [97]         | Sri Lanka          | Case study        | Community                 | Composite index (MFCSVI)               |
| 43  | Khodadad et al. (2023) [59]            | Mexico             | Review            | Regional; urban           | Composite index                        |
| 44  | Kreibich et al. (2010) [134]           | Germany            | General/technical | Infrastructure            | Damage and loss modelling (FLEMO)      |
| 45  | Laskar et al. (2021) [119]             | India              | General/technical | Infrastructure            | Dempster-Shafer evidence theory        |
| 46  | Li & Bortolot (2022) [44]              | USA                | Case study        | Regional                  | Machine learning; remote sensing       |
| 47  | Liao et al. (2022) [127]               | China (Zhejiang)   | Case study        | Regional                  | Composite index; statistical           |
| 48  | Liu, H. et al. (2022) [149]            | Japan              | Case study        | Infrastructure            | Semi-Markov recovery model             |
| 49  | Liu, T. et al. (2022) [150]            | China (Taitou)     | Case study        | Community; infrastructure | Statistical; hydraulic modelling       |
| 50  | Membele et al. (2022) [30]             | South Africa       | Review            | Community; regional       | Composite index; geospatial            |
| 51  | Moreira et al. (2021) [162]            | Brazil             | General/technical | Regional                  | Composite index                        |
| 52  | Pappalardo & La Rosa (2023) [130]      | Italy              | Case study        | Regional; urban           | Composite index; geospatial            |
| 53  | Mühlhofer et al. (2024) [40]           | Global             | General/technical | Infrastructure            | Network performance; cascading failure |

Table A5. Cont.

| No. | Author(s), Year                    | Country/Region                          | Study Type        | Application Scale         | Principal Method Family                      |
|-----|------------------------------------|-----------------------------------------|-------------------|---------------------------|----------------------------------------------|
| 54  | Museru et al. (2024) [153]         | USA (Alabama)                           | Case study        | Infrastructure            | Machine learning; damage modelling           |
| 55  | Mwale et al. (2015) [115]          | Malawi                                  | Case study        | Community                 | Composite index                              |
| 56  | Ni et al. (2010) [20]              | China                                   | Case study        | Regional                  | Composite index; machine learning (k-means)  |
| 57  | Nofal & van de Lindt (2021) [154]  | USA                                     | Case study        | Community; infrastructure | Damage and loss modelling                    |
| 58  | Kurata et al. (2023) [143]         | Philippines                             | Case study        | Community                 | Statistical (SEM)                            |
| 59  | Paleo-Torres et al. (2021) [25]    | USA                                     | General/technical | Infrastructure            | Fragility and vulnerability functions        |
| 60  | Pathak & Kulshrestha (2021) [112]  | India (Narmada)                         | Case study        | Regional                  | Composite index (RAAAR)                      |
| 61  | Pan et al. (2023) [160]            | China (Wuhan)                           | Case study        | Community                 | Composite index                              |
| 62  | Paulik et al. (2025) [155]         | Small island developing state           | Case study        | Infrastructure            | Damage and loss modelling                    |
| 63  | Posner & Georgakakos (2017) [124]  | USA                                     | Case study        | Infrastructure            | Hydraulic and hydrodynamic modelling         |
| 64  | Pricope et al. (2022) [156]        | USA                                     | Case study        | Regional                  | Composite index; geospatial                  |
| 65  | Redondo-Tilano et al. (2025) [157] | Canada                                  | Review            | Infrastructure            | Damage and loss modelling                    |
| 66  | Sadeghi-Pouya et al. (2017) [72]   | Iran (Mazandaran)                       | Case study        | Regional                  | Composite index (parametric RVS)             |
| 67  | Sadia et al. (2020) [146]          | Pakistan (Nowshera, Khyber Pakhtunkhwa) | Case study        | Community                 | Qualitative-supported index                  |
| 68  | Sakieh (2017) [45]                 | Iran                                    | Case study        | Regional; urban           | Composite index; spatial pattern analysis    |
| 69  | Scawthorn et al. (2006) [136]      | USA                                     | General/technical | Infrastructure            | Damage and loss modelling (HAZUS-MH)         |
| 70  | Schotten & Bachmann (2023) [120]   | Germany                                 | General/technical | Infrastructure            | Network performance                          |
| 71  | Shiwomeh et al. (2024) [151]       | Cameroon (Yaoundé)                      | Case study        | Community                 | Composite index; survey-based                |
| 72  | Singh & Pandey (2021) [113]        | India (Uttarakhand)                     | Case study        | Regional                  | Composite index; MCDA                        |
| 73  | Sultana & Chen (2009) [123]        | Canada                                  | Case study        | Infrastructure            | Fragility; probabilistic (Petri net; Markov) |
| 74  | Sun et al. (2022) [163]            | China                                   | Case study        | Regional; urban           | Composite index; statistical                 |
| 75  | Sweya et al. (2020) [121]          | Tanzania                                | Case study        | Infrastructure            | Composite index                              |
| 76  | Tabasi et al. (2025) [7]           | Iran                                    | Review            | Regional                  | Hierarchical risk framework                  |
| 77  | Mabrouk et al. (2024) [88]         | China                                   | Review            | Regional; urban           | Composite index; urban form indicators       |
| 78  | Tanir et al. (2021) [89]           | USA (Washington DC)                     | Case study        | Community; regional       | Composite index                              |

Table A5. Cont.

| No. | Author(s), Year                    | Country/Region                | Study Type        | Application Scale   | Principal Method Family                  |
|-----|------------------------------------|-------------------------------|-------------------|---------------------|------------------------------------------|
| 79  | Tellman et al. (2020) [164]        | USA                           | General/technical | Community           | Statistical; validation against outcomes |
| 80  | Vatenmacher et al. (2022) [122]    | Israel                        | General/technical | Infrastructure      | Performance-driven analysis              |
| 81  | Vatteri et al. (2022) [23]         | United Kingdom                | General/technical | Infrastructure      | Bayesian networks                        |
| 82  | Venkataramanan et al. (2019) [61]  | USA                           | Review            | Community           | Composite index                          |
| 83  | Wang et al. (2025) [48]            | China                         | General/technical | Infrastructure      | Network performance; cascading failure   |
| 84  | Williams et al. (2025) [125]       | New Zealand                   | General/technical | Infrastructure      | Expert-derived damage curves             |
| 85  | Yang et al. (2018) [12]            | China                         | Case study        | Regional; urban     | Fuzzy comprehensive evaluation; CDDM     |
| 86  | Bhowmik et al. (2021) [38]         | Bangladesh                    | Case study        | Community           | Composite index                          |
| 87  | Wang, L. et al. (2022) [46]        | China                         | Review            | Regional            | Composite index                          |
| 88  | Pathak, S. et al. (2020) [60]      | Nepal                         | Case study        | Community           | Composite index; statistical             |
| 89  | Yahaya et al. (2010) [76]          | Nigeria (Hadejia-Jama'are)    | Case study        | Regional            | MCDA; geospatial                         |
| 90  | Tascón-González et al. (2020) [83] | Spain                         | Case study        | Community; regional | Composite index; geospatial              |
| 91  | Zheng et al. (2008) [80]           | China (Huaihe)                | Case study        | Regional            | Land use and population analysis         |
| 92  | Jibhakate et al. (2023) [24]       | India (Surat)                 | Case study        | Regional; urban     | Composite index; MCDA                    |
| 93  | Rogers et al. (2025) [6]           | Global                        | General/technical | Regional            | Statistical; scenario modelling          |
| 94  | Safiah Yusmah et al. (2020) [22]   | Malaysia (Kuantan)            | Case study        | Community           | Composite index                          |
| 95  | Azua et al. (2019) [67]            | Nigeria (Kano)                | Case study        | Regional; urban     | MCDA; geospatial                         |
| 96  | Moreira et al. (2021) [19]         | Brazil                        | Review            | Regional            | Composite index                          |
| 97  | Shah et al. (2020) [26]            | Pakistan (Khyber Pakhtunkhwa) | Case study        | Community           | Composite index; statistical             |
| 98  | Ali et al. (2019) [69]             | India (Sundarban)             | Case study        | Regional            | MCDA (AHP); frequency ratio              |
| 99  | Baky et al. (2020) [47]            | Bangladesh                    | Case study        | Regional            | Composite index; hydraulic modelling     |
| 100 | Khajehei et al. (2020) [51]        | USA                           | General/technical | Regional            | Composite index; statistical             |
| 101 | Singh & Kumar (2019) [78]          | India (Markanda)              | Case study        | Regional            | Watershed characteristic analysis        |
| 102 | Geris et al. (2022) [53]           | Botswana                      | Case study        | Regional            | Hydrological analysis                    |
| 103 | Waseem & Rana (2023) [63]          | Pakistan                      | Review            | Regional            | Composite index                          |
| 104 | Antwi et al. (2015) [81]           | Ghana (Wa West)               | Case study        | Community           | Composite index                          |

Table A5. Cont.

| No. | Author(s), Year                        | Country/Region         | Study Type        | Application Scale         | Principal Method Family            |
|-----|----------------------------------------|------------------------|-------------------|---------------------------|------------------------------------|
| 105 | Rangari et al. (2019) [65]             | India                  | Case study        | Regional; urban           | Hydraulic modelling (HEC-RAS 2D)   |
| 106 | Parvin et al. (2016) [14]              | Bangladesh             | Case study        | Community                 | Livelihood analysis                |
| 107 | Chakraborty & Mukhopadhyay (2019) [64] | India (West Bengal)    | Case study        | Regional                  | MCDA (AHP); geospatial             |
| 108 | Ogwuche & Abah (2014) [86]             | Nigeria (Makurdi)      | Case study        | Community                 | Composite index                    |
| 109 | Pritchard & Thielemans (2014) [68]     | India (Bihar)          | Case study        | Community                 | Livelihood analysis                |
| 110 | Tran et al. (2008) [43]                | Viet Nam               | Case study        | Community; regional       | Composite index                    |
| 111 | Tanoue et al. (2016) [71]              | Global                 | General/technical | Regional                  | Statistical; time-series           |
| 112 | Taromideh et al. (2022) [79]           | Iran                   | Case study        | Regional; urban           | MCDA; machine learning             |
| 113 | Ouma & Tateishi (2014) [103]           | Kenya                  | Case study        | Regional; urban           | MCDA (AHP); geospatial             |
| 114 | Ajtai et al. (2023) [54]               | Romania                | Case study        | Community; regional       | Composite index; statistical (PCA) |
| 115 | Mishra et al. (2022) [56]              | USA                    | Review            | Regional                  | Overview of concepts and methods   |
| 116 | Sanyal & Lu (2005) [104]               | India (West Bengal)    | Case study        | Regional                  | Remote sensing; geospatial         |
| 117 | Nkeki et al. (2013) [170]              | Nigeria (Niger-Benue)  | Case study        | Regional                  | Geospatial techniques              |
| 118 | Adikari et al. (2010) [37]             | Asia (megacities)      | General/technical | Regional; urban           | Composite index                    |
| 119 | Dano et al. (2019) [110]               | Malaysia (Perlis)      | Case study        | Regional                  | MCDA (analytic network process)    |
| 120 | Wu (2021) [75]                         | USA                    | General/technical | Regional                  | Statistical (PCA)                  |
| 121 | Gounaridis et al. (2024) [142]         | USA                    | General/technical | Community; regional       | Statistical; spatial correlation   |
| 122 | Ndimele et al. (2024) [144]            | Nigeria (Lagos)        | Case study        | Community                 | Composite index                    |
| 123 | Assaad et al. (2024) [129]             | USA                    | General/technical | Infrastructure            | Data mining; cascading effects     |
| 124 | Rözer & Surminski (2021) [168]         | UK (England and Wales) | Case study        | Community; infrastructure | Statistical; scenario modelling    |
| 125 | Chanda Shimi et al. (2010) [57]        | Bangladesh             | Case study        | Community                 | Survey-based index                 |
| 126 | Njoku et al. (2017) [5]                | Nigeria (Owerri)       | Case study        | Regional; urban           | Geospatial; correlation mapping    |
| 127 | Burayu et al. (2023) [107]             | Ethiopia (Oromia)      | Case study        | Regional                  | MCDA (AHP); geospatial             |
| 128 | Abdo et al. (2025) [169]               | Eastern Mediterranean  | Case study        | Regional                  | MCDA; geospatial                   |
| 129 | Okonufua et al. (2019) [171]           | Nigeria (Ebonyi)       | Case study        | Community; regional       | Composite index                    |

**Table A5.** *Cont.*

| No. | Author(s), Year                   | Country/Region        | Study Type        | Application Scale | Principal Method Family               |
|-----|-----------------------------------|-----------------------|-------------------|-------------------|---------------------------------------|
| 130 | Mundhe (2019) [140]               | India (Pune)          | Case study        | Regional; urban   | MCDA                                  |
| 131 | Subraelu et al. (2023) [133]      | UAE (Fujairah)        | Case study        | Regional; urban   | Geospatial; remote sensing            |
| 132 | Mann & Gupta (2023) [101]         | India (Mumbai)        | Case study        | Regional; urban   | MCDA (AHP)                            |
| 133 | Aju et al. (2024) [33]            | India (Kerala)        | Case study        | Regional          | Statistical; geospatial               |
| 134 | Erena & Worku (2019) [35]         | Ethiopia (Dire Dawa)  | Case study        | Regional; urban   | Composite index; geospatial           |
| 135 | Anand & Marcotullio (2024) [8]    | USA (New York City)   | Case study        | Community; urban  | Composite index; statistical          |
| 136 | Narendr et al. (2020) [167]       | India                 | Case study        | Regional          | Composite index; land-use modelling   |
| 137 | Nithyanandham et al. (2023) [102] | India                 | General/technical | Regional          | MCDA (fuzzy graph)                    |
| 138 | Susilawati et al. (2025) [131]    | Indonesia             | Case study        | Community         | Composite index; survey-based         |
| 139 | Koutsovili et al. (2023) [36]     | Greece                | Case study        | Regional          | Participatory; nature-based solutions |
| 140 | Ashmawy et al. (2000) [34]        | Egypt (Sinai)         | Case study        | Regional          | Geospatial; drainage basin analysis   |
| 141 | Ahmed et al. (2022) [74]          | Bangladesh            | Case study        | Regional          | Composite index; geospatial           |
| 142 | Youssef et al. (2023) [55]        | Egypt                 | Case study        | Regional          | Machine learning (FR; LR; SVM)        |
| 143 | Rahman et al. (2016) [15]         | Saudi Arabia (Riyadh) | Case study        | Regional; urban   | Composite index; geospatial           |
| 144 | Abdelkareem & Mansour (2023) [50] | Egypt                 | Case study        | Regional          | Geospatial; knowledge-driven          |

## Appendix B. Method Workflow Diagrams

The figures in this appendix document the analytical workflow of individual quantification methods discussed in Section 4. They are reproduced here, rather than within the Results, so that the comparative narrative of that section is not interrupted; each is cross-referenced from the corresponding passage. The diagrams are ordered by application scale, and record for each method the sequence of operations, the points at which expert judgement or data-derived weighting enters, the treatment of uncertainty where applicable, and the form of the classified output.

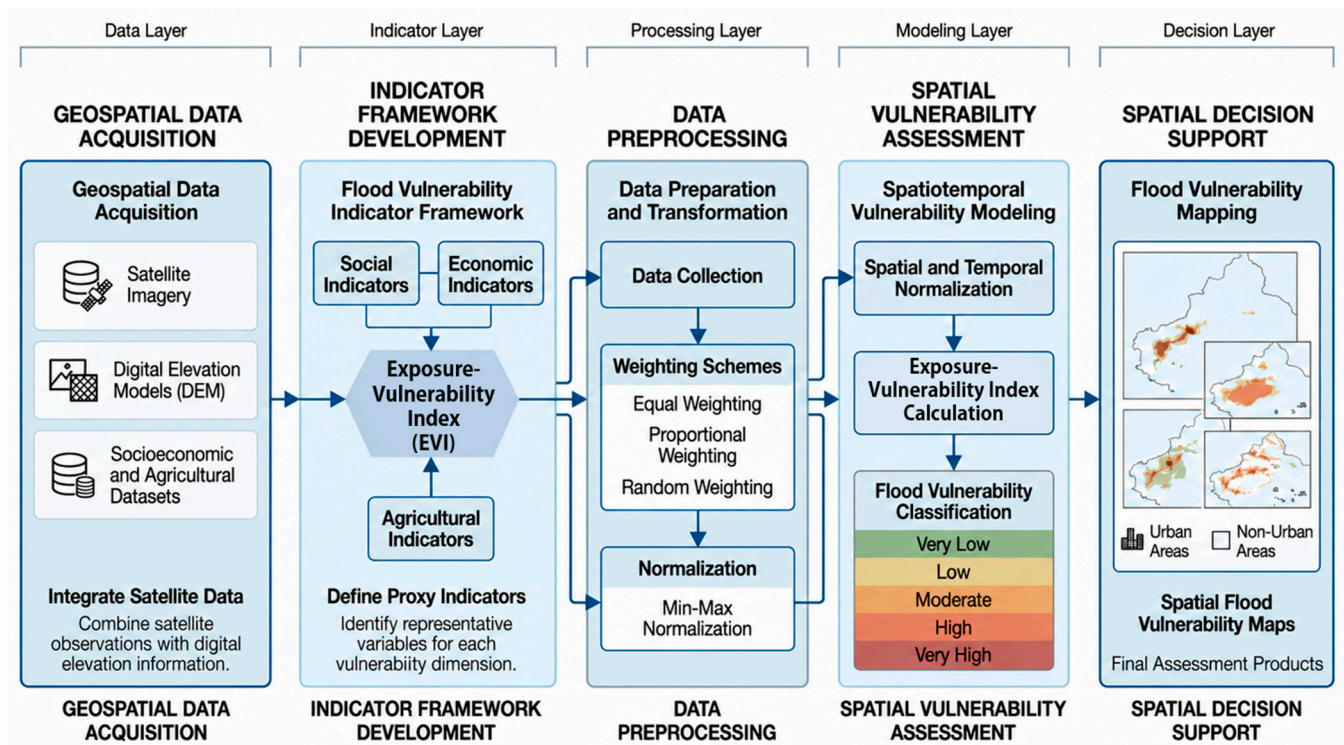


**Figure A1.** The process of digital elevation methods using satellite-based data to find flood vulnerability.

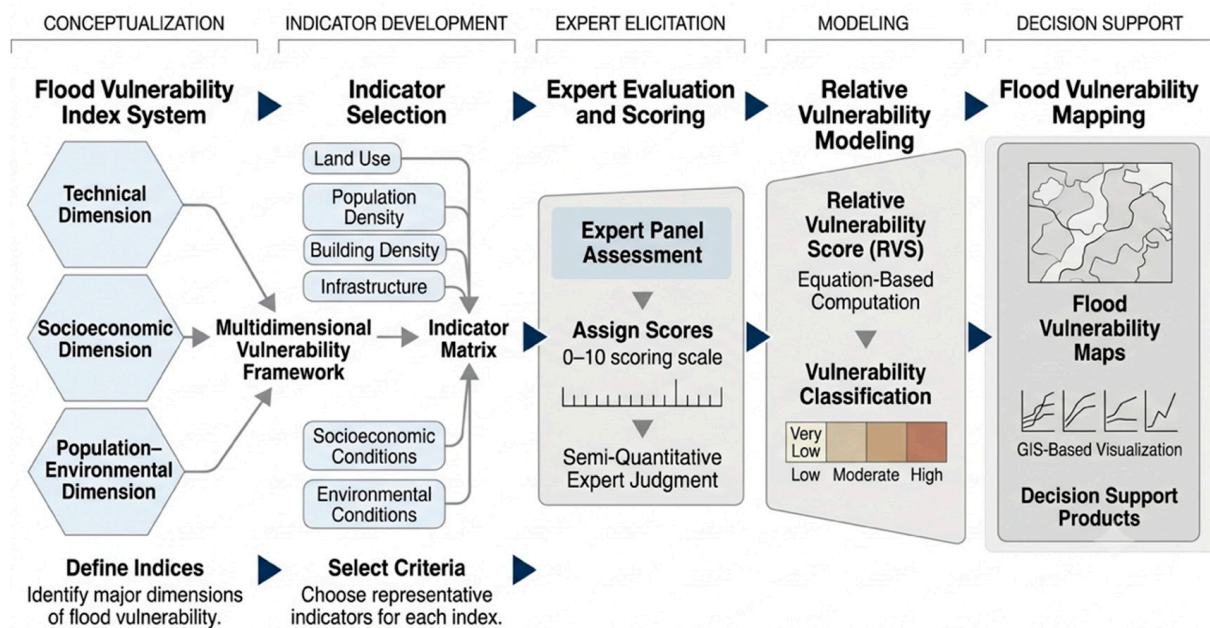


**Figure A2.** Expert knowledge-based framework of the parametric approach for flood vulnerability assessment, illustrating the transformation of multidimensional vulnerability concepts into relative vulnerability scores and classified GIS-based vulnerability maps through indicator selection, expert scoring, and semi-quantitative modeling.

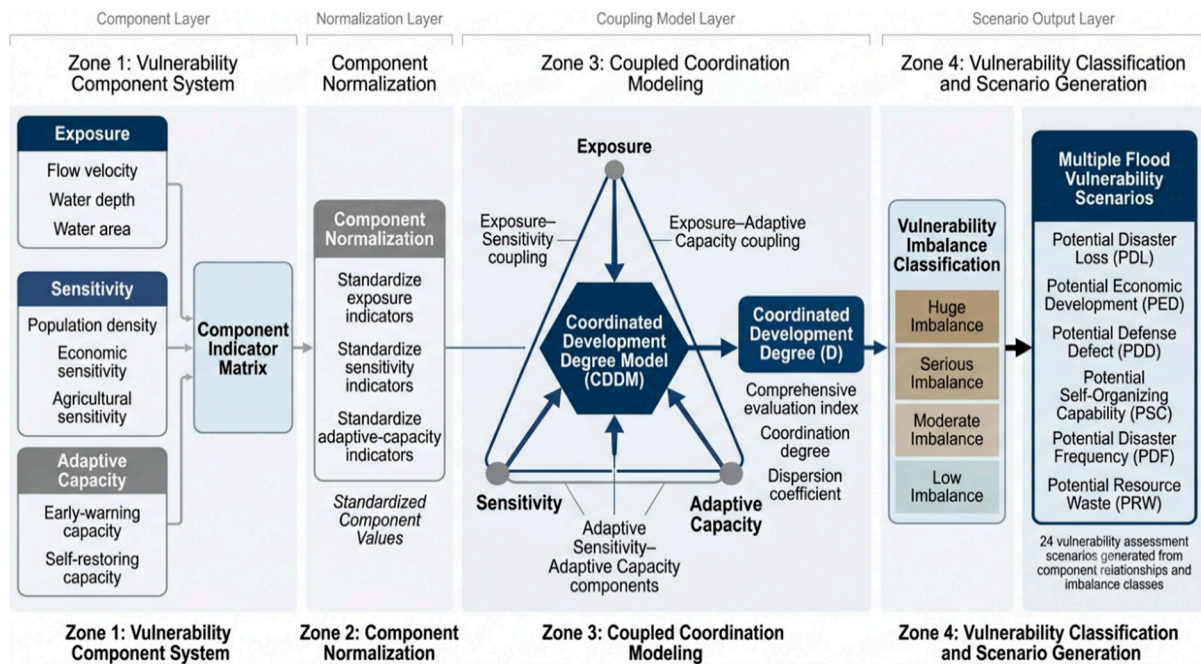


**Figure A3.** Coupled-systems framework for multiple flood vulnerability assessment using the Coordinated Development Degree Model (CDDM). The framework illustrates how exposure, sensitivity, and adaptive capacity are standardized and integrated through pairwise coordination relationships to quantify coordinated development degrees and generate scenario-based flood vulnerability assessments.

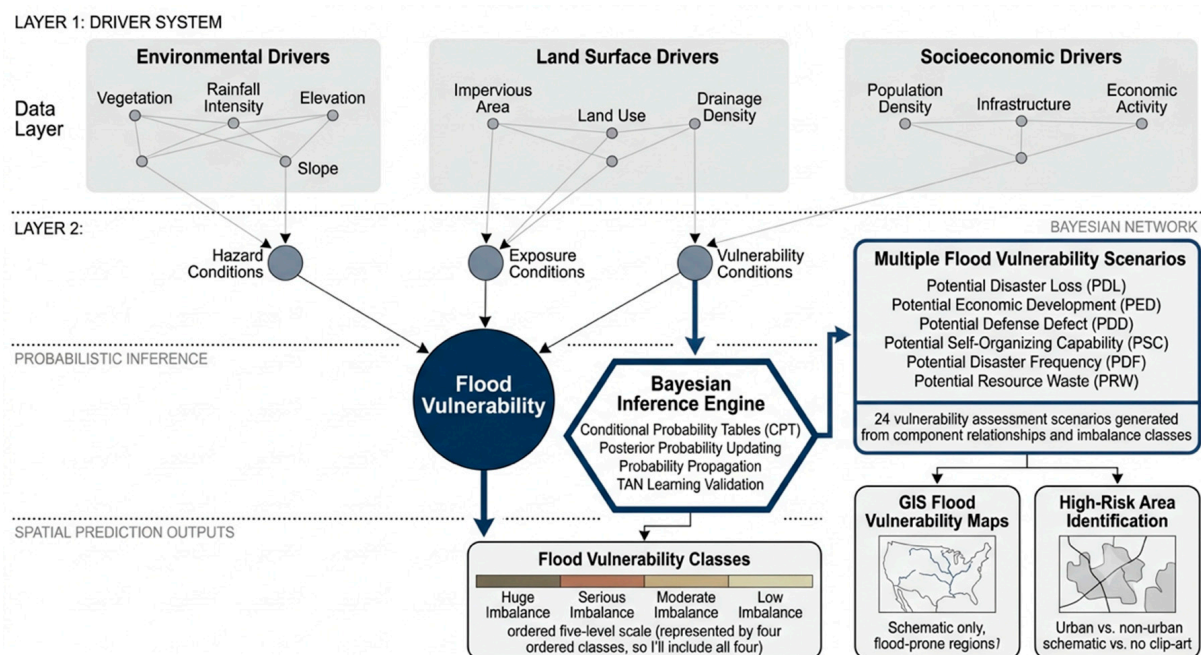


**Figure A4.** Probabilistic network framework of the Bayesian Belief Network (BBN) approach for pluvial flood vulnerability assessment [21]. The framework illustrates the transformation of 17 bio-physical and land-cover vulnerability variables, including impervious surface, vegetation coverage, drainage density, and rainfall intensity, into posterior flood vulnerability probabilities through conditional probability estimation, TAN structure learning, and GIS-based spatial mapping of classified urban flood vulnerability zones.

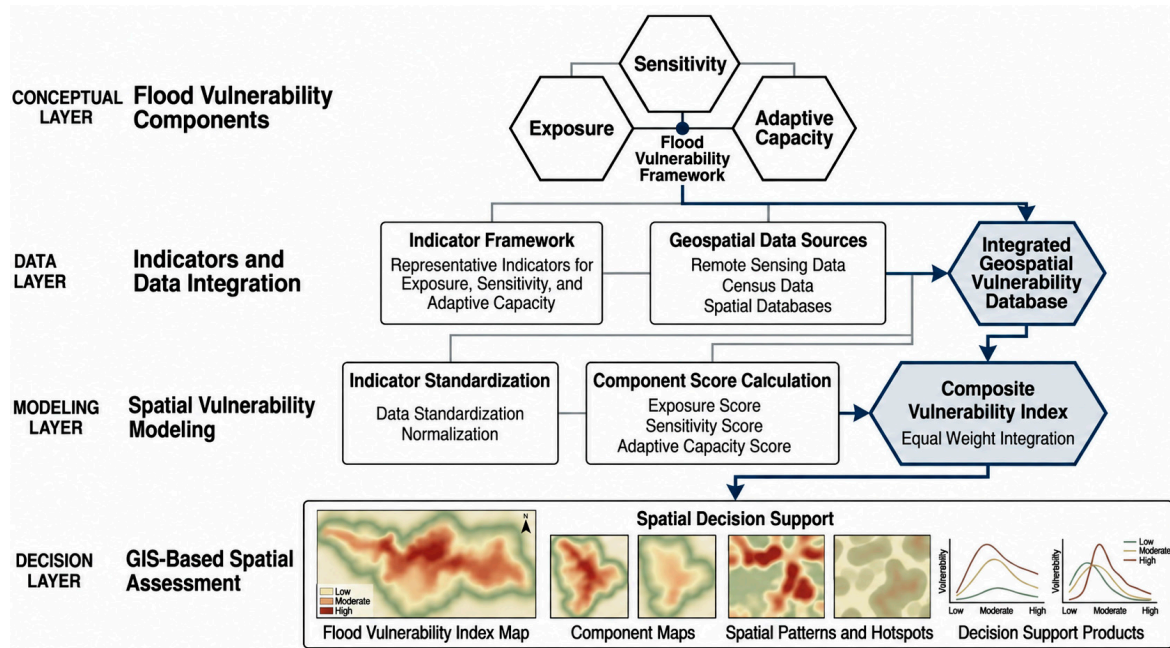


**Figure A5.** GIS-based framework linking multidimensional geospatial inputs to standardized vulnerability components, a composite index, and spatial decision-support maps.

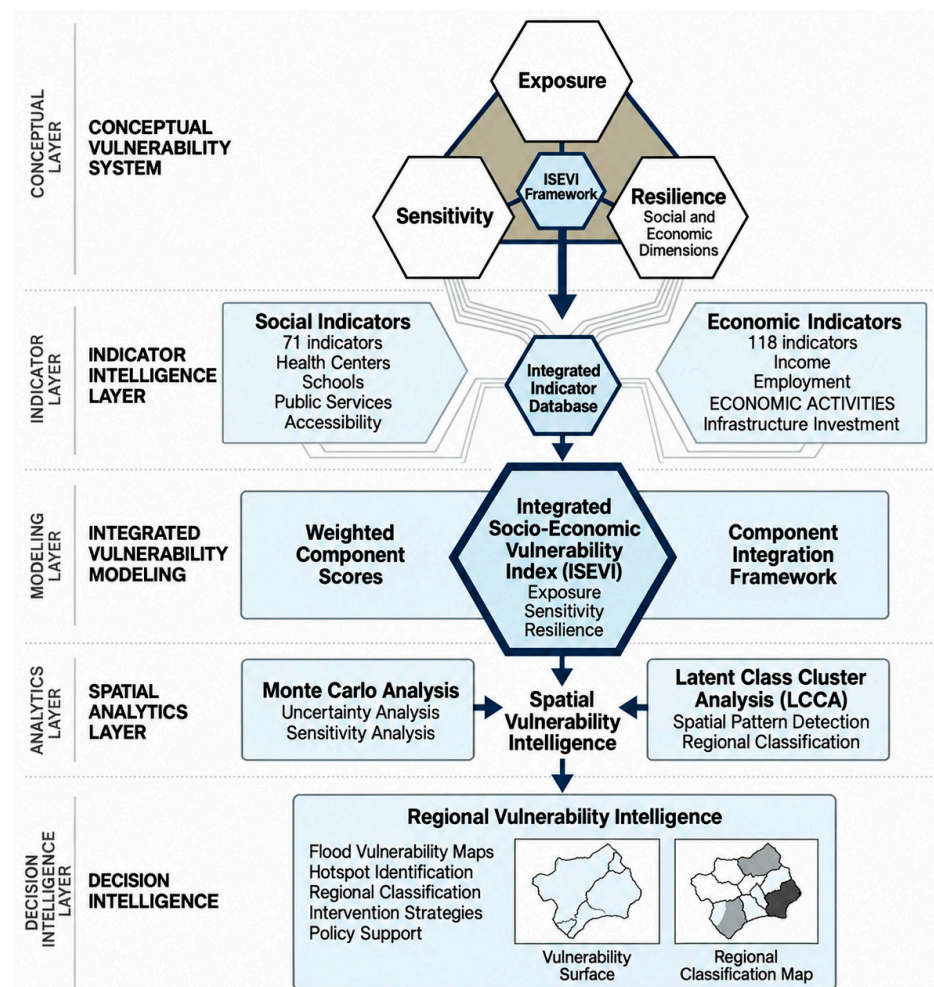


**Figure A6.** Workflow for developing and validating the Integrated Socio-Economic Vulnerability Index using weighted component modeling, Monte Carlo uncertainty analysis, latent-class clustering, and GIS mapping.

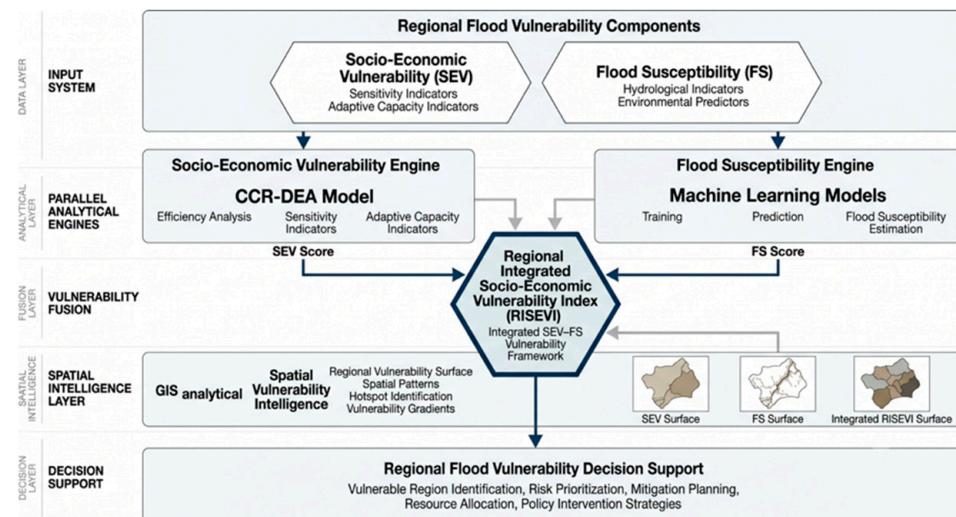


**Figure A7.** Hybrid artificial intelligence framework for quantifying the Regional Integrated Socio-Economic Vulnerability Index (RISEVI). The framework integrates socio-economic vulnerability assessment using the CCR-DEA model and machine-learning-based flood susceptibility estimation to generate spatial vulnerability intelligence and GIS-supported decision products for regional flood vulnerability management.

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