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Review

Cognitive and Organisational Dynamics of Decision-Making in Urban Flood Emergencies for Sustainable and Resilient Cities: A Systematic Review

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Abstract

Urban flood events are increasing in frequency and severity, threatening the social, economic and environmental sustainability of cities and placing considerable strain on decision-makers operating in complex and high-pressure environments. While the technical and infrastructural aspects of flood response have been widely examined, systematic attention to the psychological and organisational dimensions of decision-making during flood emergencies remains limited. This study synthesises the existing literature on how cognitive, psychological, institutional, technological, and social factors influence decision-making under pressure in urban flood contexts. A systematic literature review (SLR) was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure a transparent, rigorous, and reproducible study-selection process. Peer-reviewed studies published between 2009 and 2026 were retrieved from the Scopus database and screened against predefined eligibility criteria. The search initially identified 376 records. After removing 5 duplicates, 371 records underwent title and abstract screening, of which 8 were excluded. The remaining 363 articles were assessed for full-text eligibility, resulting in the exclusion of 133 articles and the inclusion of 230 studies in the final synthesis. Thematic analysis was employed to identify key decision-making variables, which were subsequently modelled using Vensim to map causal relationships and feedback mechanisms among cognitive stressors, organisational conditions, technological factors, and decision quality. The findings reveal that communication breakdowns can amplify role ambiguity and diminish situational awareness, creating reinforcing cycles that undermine decision quality. Stress-induced cognitive limitations and institutional fragmentation also emerged as important influences on response effectiveness. Overall, urban flood emergency decision-making is shaped by interconnected relationships among cognitive load, time pressure, leadership clarity, institutional coordination, technological support, and organisational structures. By integrating behavioural, organisational, technological, and social dimensions, this study provides a systems-based understanding of urban flood emergency decision-making and identifies critical intervention points for strengthening real-time response effectiveness. Because the quality of emergency decisions determines whether lives, livelihoods, infrastructure and ecosystem services are protected, and whether these protections are distributed equitably, the findings position flood emergency decision-making as a core component of sustainable urban development and support progress towards Sustainable Development Goals 11 (Sustainable Cities and Communities) and 13 (Climate Action) and the Sendai Framework for Disaster Risk Reduction.

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1. Introduction

Urban flooding is among the most disruptive climate-related hazards, and emergency decisions are increasingly made in conditions of uncertainty, time pressure, cascading infrastructure impacts, and rapidly changing information [1–3]. Recent work further shows that the frontier is moving from prediction alone toward near-real-time and prescriptive decision support, including GPU-accelerated forecasting, knowledge-graph emergency planning, and AIoT-enabled impact mapping [4–6]. Yet technical capability is only one part of response effectiveness: human cognition, institutional coordination, communication, and trust determine whether information is converted into timely action. Recent studies further emphasise that effective flood risk management depends not only on technical forecasting capabilities but also on how uncertainty is addressed in planning and decision-making [7]. Equally important are behavioural factors, particularly how individuals interpret, trust, and respond to flood risk information, which can significantly influence preparedness and mitigation decisions [8].

Urban flood emergency decision-making is also a sustainability issue. Decisions taken in the hours before and during a flood determine whether lives, livelihoods, critical infrastructure and ecosystem services are protected, and therefore whether development gains are preserved or lost [2]. Delayed or poorly coordinated decisions impose social costs that fall disproportionately on low-income and marginalised groups, economic costs through damage to housing, businesses and infrastructure, and environmental costs through pollution, debris and the disruption of urban water systems [2,9]. Conversely, timely, well-coordinated and equitable decisions reduce losses, accelerate recovery and build the institutional capacity on which long-term adaptation depends. The quality of emergency decision-making is therefore a practical determinant of the social, economic and environmental dimensions of urban sustainability, linking short-term crisis response to the long-term goal of sustainable and resilient cities.

The complexity of urban flood decision-making stems from its multifaceted nature. Decision-makers must process incomplete or ambiguous information, coordinate across organisational boundaries, manage limited resources, and balance competing priorities while operating under significant psychological pressure [9,10]. These challenges are exacerbated by the unpredictable progression of flood events, where conditions can rapidly change and render previous assessments invalid [11]. Urban flooding presents decision complexities that distinguish it from other emergency contexts. Unlike more contained disasters, floods typically affect large geographic areas simultaneously, creating distributed decision-making challenges across multiple jurisdictions [12]. The temporal dimension of flooding, with precursor conditions developing over hours or days before peak impact, creates a decision window characterised by escalating certainty about the event, coupled with diminishing response options [13]. This temporal aspect introduces unique psychological pressures as decision-makers must determine when to commit resources or order evacuations based on probabilistic forecasts rather than observed conditions [14].

The institutional context further complicates flood response decision-making. Modern flood management operates within complex governance frameworks that span multiple organisations with different mandates, resources, and decision-making protocols [15]. This institutional complexity introduces coordination challenges that can impede timely and

coherent response efforts [16]. A recent study of emergency managers and health professionals found that communication inefficiencies, jurisdictional confusion and inadequate situational awareness continue to undermine inter-agency response [17]. Additionally, political considerations often influence flood response decisions, as public officials must navigate stakeholder concerns, resource allocation trade-offs, and potential liability issues while under intense public scrutiny [18]. Psychological factors significantly influence decision quality during flood emergencies. Stress affects cognitive processes by narrowing attention, reducing working memory capacity, and biasing information processing [19]. Research demonstrates how high-stress environments can lead emergency managers to revert to familiar but potentially suboptimal response patterns rather than adapting to novel situations [20]. Sleep deprivation, common during extended emergency operations, further degrades decision-making capabilities through impaired executive function and emotional regulation. Cognitive biases also influence flood response decisions [21]. Confirmation bias leads decision-makers to selectively attend to information that aligns with their initial assessment while discounting contradictory evidence. Availability bias may cause overweighting of recent flood experiences, potentially leading to either overreaction or underreaction depending on the decision-maker's history [22]. Group dynamics introduce additional complexities, including groupthink and authority gradient effects, which can suppress dissenting viewpoints that might otherwise reveal flawed assumptions or overlooked alternatives. Investigations conducted within related disciplines, such as disaster management, cognitive psychology, and organisational behaviour, provide critical insights into the nuances of decision-making in high-pressure situations [12]. Studies of naturalistic decision-making demonstrate how experienced professionals rely on pattern recognition and mental simulation rather than formal analytical processes when facing complex situations under time constraints. Similarly, work on sensemaking highlights how individuals and organisations construct meaning during crisis events to inform their actions [23].

However, as Parmar et al. [24] observe, these theoretical frameworks have not been systematically applied to understand the specific challenges of urban flood decision-making. The unique aspects of flood emergencies, including their spatial and temporal unpredictability, cascading infrastructure failures, and public response dynamics, create distinctive decision environments that merit dedicated study [25]. This research directly addresses the 2030 Agenda for Sustainable Development [26] and two of its Sustainable Development Goals (SDGs). Primarily, it contributes to SDG 11 (Sustainable Cities and Communities), specifically target 11.5, which aims to "significantly reduce the number of deaths and people affected by disasters, including water-related disasters" [22,27]. By examining how decisions are made during urban flood events, this work also supports target 11.b, which calls for "substantially increasing the number of cities and human settlements adopting and implementing integrated policies and plans towards inclusion, resource efficiency, mitigation and adaptation to climate change, and resilience to disasters" [28]. Additionally, this research advances SDG 13 (Climate Action), particularly target 13.1, which emphasises "strengthening resilience and adaptive capacity to climate-related hazards and natural disasters" [21].

The study also responds to the Sendai Framework for Disaster Risk Reduction 2015–2030 [29], whose priorities of strengthening disaster risk governance and enhancing disaster preparedness for effective response correspond directly to the organisational, institutional and cognitive dimensions examined here. Sustainability in this context has three interrelated aspects: social sustainability, through equitable access to timely warnings and protective action for vulnerable communities; economic sustainability, through reduced losses and faster recovery of urban functions; and environmental sustainability, through the protection of urban water systems, ecosystems and the services they provide. By treating the human and institutional side of flood response as part of sustainable urban development

rather than solely as an operational concern, the review connects emergency management research with the wider sustainability and climate adaptation agendas.

As climate change intensifies precipitation patterns and increases flood risks in urban areas, understanding and improving decision processes becomes a central adaptation strategy and a prerequisite for sustainable urban development. Given these interconnected challenges and the critical need to enhance urban flood resilience across multiple dimensions, from reducing disaster impacts to strengthening adaptive capacity, a comprehensive examination of decision-making processes is essential [16,30]. These intersecting cognitive, institutional, and technical pressures create a decision environment that remains systematically underexplored. This study therefore aims to synthesise existing literature on how cognitive, psychological, and institutional factors influence decision-making under pressure in urban flood contexts, with the goal of identifying critical feedback mechanisms and intervention points for improving real-time response. Training programmes that incorporate realistic simulations help decision-makers develop recognition-primed decision-making skills that transfer to actual emergencies [31]. These approaches align with recognition-primed decision models, which emphasise the importance of experience-based pattern recognition in high-pressure environments. Structured decision protocols can counteract cognitive biases by prompting systematic consideration of alternatives and explicit evaluation of assumptions [30]. Technological innovations also support improved decision-making. Advanced decision support systems now integrate real-time monitoring data, predictive modelling, and visualisation tools to enhance situational awareness [1,11].

However, research cautions that technology must be designed with attention to human cognitive limitations to avoid information overload or automation bias [32]. Organisational structures and processes have a significant influence on decision effectiveness during flood emergencies. High-reliability organisation principles, including preoccupation with failure, reluctance to simplify, sensitivity to operations, commitment to resilience, and deference to expertise, provide valuable frameworks for flood response organisations [33]. Similarly, adaptive management approaches that emphasise flexibility, learning, and decentralised authority enable more agile responses to dynamic flood conditions [34]. Therefore, this study systematically analyses the interdependence between cognitive, psychological, and institutional factors in urban flood emergency decision-making processes, with the wider aim of supporting decision processes that protect the social, economic and environmental foundations of sustainable cities.

The review is structured in two complementary analytical stages. Section 3 provides a thematic synthesis across all 230 publications organised by the four primary dimensions of flood emergency decision-making. Section 4 then conducts a focused evolutionary analysis of a contemporary subset (208 studies published between 2014 and 2026) to track how the relative prominence of specific operational factors has shifted over time. This two-stage structure allows both conceptual depth (Section 3) and temporal granularity (Section 4) to be achieved within a single review. Through the synthesis of diverse literature using systems modelling, this research aims to identify critical feedback mechanisms, decision thresholds, and intervention points that can improve the quality of real-time decision-making during flood events. The specific objectives of this study are:

1. To systematically analyse the interdependence between cognitive, psychological, and institutional factors in urban flood emergency decision-making processes.
2. To develop an integrated framework that acknowledges the complex interplay between cognitive limitations, institutional structures, and technological capabilities, as a basis for more sustainable and resilient urban flood management.
3. To identify critical feedback mechanisms that influence the quality of decision-making during urban flood events.

2. Research Methodology

This study employed a systematic literature review (SLR) methodology aligned with the PRISMA 2020 guidelines. PRISMA was adopted to enhance transparency, reproducibility, and systematic reporting across the stages of study identification, screening, eligibility assessment, and final inclusion. The review focused on multidisciplinary research concerning decision-making in urban flood emergencies and covered peer-reviewed literature published between 2009 and 2026. Following the complete screening and eligibility assessment process, 230 studies were retained for thematic synthesis and systems-based analysis.

2.1. Search Strategy and Database

A comprehensive literature search was conducted in 2026 using Scopus. Scopus was selected because of its broad interdisciplinary coverage of relevant fields, including disaster and emergency management, cognitive psychology, urban planning, engineering, governance, organisational behaviour, and decision sciences. The search strategy incorporated three interconnected conceptual domains: (1) decision-making and cognition, (2) urban flooding and flood emergencies, and (3) organisational or institutional emergency management. Core search terms included "decision-making," "decision support," "cognitive process," "psychological factor," "situational awareness," "urban flood," "flood emergency," "flood response," "governance," "multi-agency," "institutional framework," and "emergency management." Synonyms within each conceptual domain were combined with the Boolean operator OR, and the three domains were combined with AND. The query was applied to the title, abstract and keyword fields, so that every retrieved record had to contain at least one decision-making term, one flood term and one emergency-management or governance term. This field-restricted, three-block structure meant that the retrieved set was already narrowly topical before screening began. The search was restricted to publications from 2009 to 2026 and initially identified 376 records. The search strategy was refined iteratively to achieve an appropriate balance between comprehensiveness and relevance to decision-making processes occurring before and during urban flood emergencies.

To make the search fully reproducible, the complete Boolean search string, as entered in the Scopus Advanced Search interface. Quotation marks force phrase matching truncates terms to capture plural and variant forms (for example, flood emergency and flood emergencies), OR combines synonyms within each conceptual block, AND requires every record to match all three blocks, and the TITLE-ABS-KEY field code restricts matching to titles, abstracts and keywords: TITLE-ABS-KEY ((“decision-making” OR “decision making” OR “decision support” OR “cognitive process” OR “psychological factor” OR “situational awareness”) AND (“urban flood” OR “flood emergenc” OR “flood response”) AND (“governance” OR “multi-agency” OR “institutional framework” OR “emergency management”)) AND PUBYEAR > 2008 AND PUBYEAR < 2026.

2.2. Inclusion and Exclusion Criteria

Predefined inclusion and exclusion criteria were applied consistently throughout the title, abstract, and full-text screening stages. Studies were included if they were peer-reviewed journal or review articles published in English between 2009 and 2026 and substantively addressed decision-making within the context of urban flood emergencies. Eligible studies were required to examine at least one of four principal dimensions: cognitive/psychological, organisational/institutional, technological, or social/community factors. Studies were excluded if they were published in languages other than English, fell outside the specified review period, or consisted of conference proceedings, book reviews, editorials, or other non-eligible publication types. Studies primarily concerned with hydrological modelling, engineering or infrastructure solutions, flood-hazard assessment, or post-disaster recovery

were also excluded when they did not substantively examine decision-making in urban flood emergencies.

The same eligibility criteria were applied at both screening stages, but the burden of proof differed between them. At the title and abstract stage, a record was excluded only when its title and abstract made it unambiguous that a criterion was not met (for example, an ineligible publication type, a hazard other than flooding, or a purely physical-science topic with no reference to decisions, planning or management). Records whose abstracts referred to decision support, planning, management or governance, but did not make clear whether decision-making in urban flood emergencies was examined substantively, were retained for full-text assessment so that potentially relevant studies were not excluded on the basis of incomplete abstract information. Table 1 presents the inclusion and exclusion criteria applied in the systematic literature review.

Table 1. Inclusion and Exclusion Criteria for the Systematic Literature Review.

Inclusion Criteria	Exclusion Criteria
Peer-reviewed journal and review articles	Conference proceedings, book reviews, and editorial commentaries
Published in English between 2009 and 2026	Non-English publications or studies outside 2009–2026
Urban flood emergency decision-making as a substantive focus	Hydrological modelling or engineering-only studies without decision-making content
Cognitive/psychological, organisational/institutional, technological, or social/community dimensions	Post-disaster recovery studies without substantive emergency decision-making analysis

2.3. Data Extraction

Data were extracted from each of the 230 included studies using a structured coding framework developed to ensure consistency across the review corpus. The extraction process captured key publication characteristics, geographical context, theoretical orientation, methodological approach, decision-making context, and the principal factors reported to influence decisions during urban flood emergencies. Each included study was subsequently classified according to four primary analytical dimensions: cognitive/psychological, organisational/institutional, technological, and social/community. These dimensions served as the overarching analytical framework, while more specific sub-themes were developed inductively through the identification of recurring concepts, patterns, relationships, and findings during the full-text analysis. To enhance methodological rigour and minimise potential bias, two members of the research team independently conducted the screening and thematic coding processes. Each study was assessed against the inclusion and exclusion criteria to determine its eligibility and relevance to the objectives of the review. Any differences in judgement were discussed among the three reviewers until a consensus was reached. Microsoft Excel from Scopus database was used to document the screening decisions and final study selection. All three reviewers agreed on the final set of eligible studies.

2.4. Thematic Synthesis and Vensim Analysis

Thematic synthesis was employed to identify recurring patterns, relationships, methodological developments, and research gaps across the 230 included studies. A hybrid deductive-inductive analytical approach was adopted. The four predefined dimensions (cognitive/psychological, organisational/institutional, technological and social/community) provided the deductive coding structure, while specific themes and sub-themes emerged

inductively from the reviewed evidence. Following thematic synthesis, literature-derived variables and relationships were transferred to Vensim to develop systems-based representations of the factors influencing decision-making during urban flood emergencies. The direction of each relationship was determined from evidence reported within the included studies and cross-checked against the coded classification matrix. The resulting diagrams are qualitative causal loop diagrams (CLDs); no stock-and-flow simulation, parameter estimation or sensitivity analysis was performed.

Link polarity followed standard CLD conventions. A positive link (+) was assigned where the reviewed evidence indicated that an increase in one variable is associated with an increase in another (or a decrease with a decrease), and a negative link (−) where an increase in one variable is associated with a decrease in another. Connections labelled N denote unsigned, context-dependent links: relationships that were consistently reported in the literature, but whose direction of effect differed between studies or depended on a third condition (for example, whether organisational structures support or burden individual decision-makers depends on whether roles are clear or authority is fragmented). Unsigned links are retained in the diagrams to preserve these documented associations, but they were excluded when determining loop polarity; reinforcing and balancing loops were identified only from closed chains of signed (+/−) links.

2.5. PRISMA Flow Diagram and Study Selection

The systematic search of Scopus initially identified 376 records. Before screening, 5 duplicate records were removed, leaving 371 unique records for title and abstract screening. During this stage, 8 records were excluded because they did not meet the predefined eligibility criteria, resulting in 363 articles proceeding to full-text assessment. The comparatively small number of exclusions at this stage reflects two features of the process. First, the field-restricted, three-block query (Section 2.1) required every record to contain decision-making, flood and emergency-management terms, so the retrieved set was already narrowly topical. Second, under the decision rule described in Section 2.2, records were excluded at title and abstract level only when ineligibility was unambiguous; many abstracts referred to decision support, planning or management without indicating whether decision-making during urban flood emergencies was examined substantively, and this could be judged only from the full text. The main attrition therefore occurred, by design, at the full-text stage. The full texts of these 363 articles were assessed against the predefined inclusion and exclusion criteria. Following full-text assessment, 133 articles were excluded because they did not substantively address decision-making in urban flood emergencies or otherwise failed to satisfy the eligibility criteria. The excluded studies primarily focused on hydrological modelling, engineering or infrastructure solutions without substantive decision-making content, flood-hazard assessment, post-disaster recovery, or other topics outside the scope of the review. The counts at each stage were rechecked and are internally consistent ($376 - 5 = 371$; $371 - 8 = 363$; $363 - 133 = 230$). Consequently, 230 studies met all eligibility requirements and were included in the final systematic review, thematic synthesis, and systems-based analysis. Figure 1 presents the PRISMA flow diagram, which transparently documents the identification, screening, eligibility, and inclusion stages of study selection; the completed PRISMA checklist is provided in the Supplementary Materials.

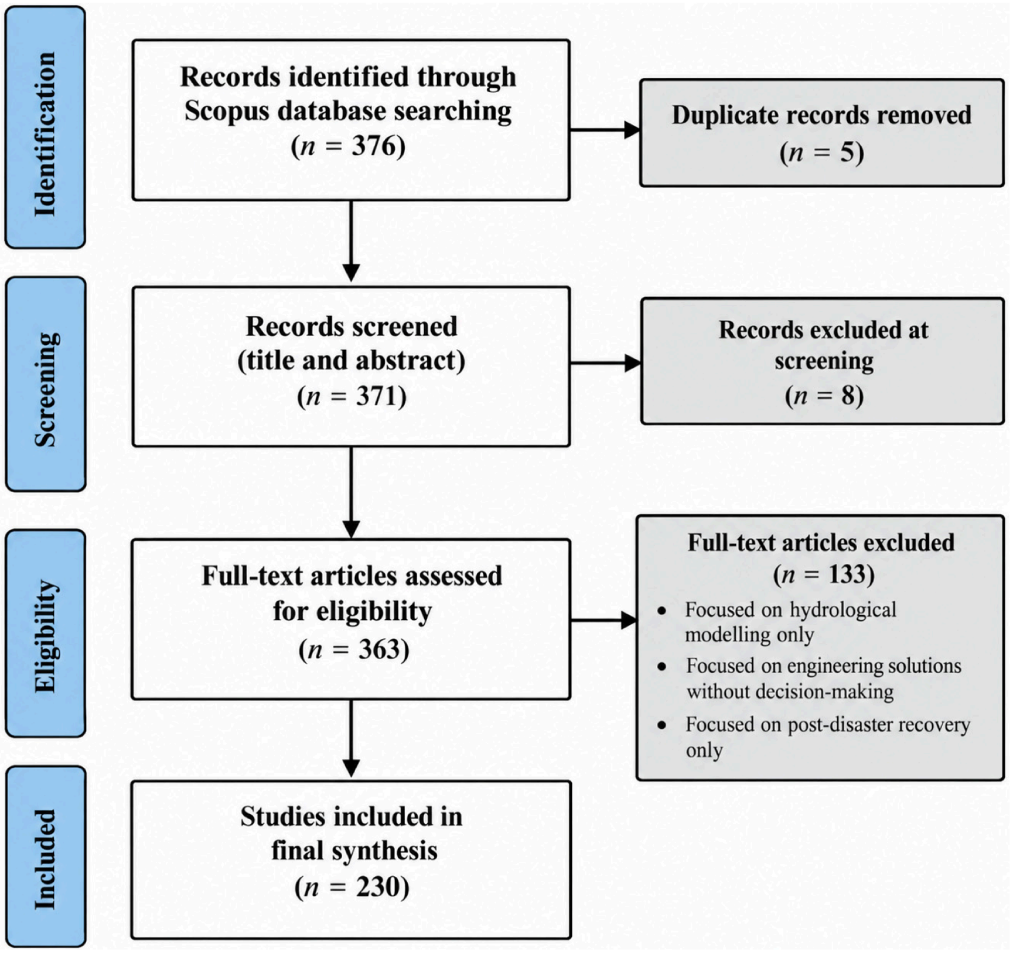

Figure 1. PRISMA Flow Diagram for the Systematic Literature Review.

3. Findings and Results

3.1. Decision-Making in Urban Flood Emergencies

The 230 included publications span the period of 2009–2026 and represent contributions from at least 47 countries and territories, with Europe and North America dominating the earlier period (2009–2018), while Asia, particularly China, accounted for 39% (21 of 54) of the coded studies published between 2024 and 2026. Methodologically, the corpus comprises empirical studies (approximately 58%), modelling-based analyses (approximately 26%), and review/conceptual studies (approximately 16%). All 230 publications were classified using a four-dimensional analytical framework comprising cognitive/psychological, organisational/institutional, technological, and social/community dimensions. The framework was developed deductively from the literature on emergency decision-making and refined iteratively during the screening and analysis processes. These four dimensions served as the primary coding categories, while more specific sub-themes emerged inductively through full-text analysis.

Section 3 synthesises the literature on decision-making in urban flood emergencies, highlighting the key themes, patterns, and factors influencing decision processes across the reviewed studies. Section 3.2 examines cognitive and psychological dimensions of decision-making; Section 3.3 addresses organisational and institutional factors; Section 3.4 covers technological dimensions and decision support systems; Section 3.5 focuses on social and community dimensions; and Section 3.6 reviews methodological approaches used in the field. For each theme, a summary table and Vensim-derived causal diagram are provided. For the cognitive and psychological dimension, whose sub-factors are aggregated

rather than modelled separately, the corresponding diagram is the integrative overview model, which links all four dimensions to decision quality under pressure and is therefore not specific to cognitive and psychological factors. Section 4 then narrows the analytical lens to the 208 studies published between 2014 and 2026 that reported at least one of ten operational factors, to trace how the prominence of these factors changed over time.

Vensim was used in this study solely as a diagramming environment for qualitative causal loop diagrams. Its notation for variables, signed links and feedback loops makes the structure of the synthesised relationships explicit and open to inspection. Although Vensim also supports stock-and-flow simulation, sensitivity analysis and Monte Carlo testing, these functions were not used, because the reviewed studies do not provide commensurable parameters from which a quantitative simulation model could be estimated. The diagrams are therefore qualitative and hypothesis-generating, and the evidence underlying their links is classified as described in Section 2.4.

3.2. Cognitive and Psychological Dimensions of Flood Decision-Making

The cognitive and psychological factors reviewed in this section represent both challenges and adaptive responses identified in the corpus. While the majority of early studies (2009–2015) focused on documenting the existence and consequences of cognitive limitations in flood decision-making, a growing body of work from 2016 onward addresses mitigation strategies including recognition-primed decision training, structured decision protocols, and stress inoculation techniques. Each factor in Table 2 is therefore understood as a challenge with associated evidence-based interventions.

The literature on cognitive processes during flood emergencies has drawn extensively from naturalistic decision-making (NDM) research, which examines how experienced professionals make decisions in high-stakes, time-pressured environments. Klein's [35] recognition-primed decision model provides a foundational framework, describing how emergency responders rely on pattern recognition rather than comprehensive analysis when facing complex and urgent situations. Recent applications of this model by de Albuquerque et al. [36] demonstrate its continued relevance in designing multicriteria decision frameworks for flood emergency preparedness. Empirical studies confirm this pattern in flood contexts, finding that experienced emergency managers typically consider only 2–3 options rather than conducting exhaustive analyses of all possibilities. Studies of experienced emergency decision-makers indicate that they typically consider only a small number of options rather than conducting exhaustive analyses of all possibilities [35]. This approach enables rapid decision-making but becomes vulnerable when faced with novel flood scenarios that do not align with previous experiences [37].

Psychological stress has a significant impact on cognitive performance during flood emergencies. Research by Xie and Shu [13] documented how acute stress narrows attention, reduces working memory capacity, and increases reliance on habitual responses during rainstorms and flood events. Their analysis using random forest algorithms identified stress as a key variable affecting decision quality in mountainous urban regions. Similarly, Huang et al. [38] analysed the spatiotemporal characteristics of emergency information during disasters and found that cognitive capacity diminishes during prolonged flood operations, impacting emergency rescue coordination. These cognitive limitations help explain why decision quality often deteriorates as flooding progresses, particularly in complex urban environments [13].

Research on risk perception has identified systematic biases relevant to flood decision-making. Parmar et al. [24] demonstrated how emergency managers tend to overweight recent experiences, leading to either over-response or under-response based on recent flood history rather than objective risk assessment. This availability heuristic manifests when

decision-makers overestimate the likelihood of events that come easily to mind. Semnan et al. [10] found that information sources significantly influence flood-coping appraisal, with personal experience often outweighing statistical risk data in shaping mitigation behaviour. Similarly, Butt et al. [22] documented how public officials who had personally experienced glacial lake outburst floods were significantly more likely to implement protective measures compared to those without direct experience, even when objective risk assessments were identical.

Risk perception also operates among decision-makers and responders themselves, not only among the public. In a survey of Australian State Emergency Service personnel, Ahmed et al. [39] found that more than half of respondents had driven through floodwater in the previous two years, even though their agencies promote policies of not entering floodwater, and that organisational factors, training and safety norms, an external locus of control and the absence of risk signals had the greatest influence on the risk perceptions that led to these decisions. Brillinger et al. [40] similarly showed, through interviews with flood risk management plan-makers, that individual beliefs shape which measures decision-makers include in flood risk management plans. Decision-makers' risk perception is therefore included in Table 2 as a cognitive factor in its own right, distinct from public risk perception, which is reported among the social and community determinants of warning response (Table 5).

Communication of uncertainty presents challenges in flood contexts. Shu et al. [23] found that emergency managers received probability-based forecasts but frequently translated these into binary decisions without fully accounting for uncertainty ranges in hydrological processes. Their uncertainty analysis of low-impact development revealed significant gaps between how uncertainty is modelled and how it is operationalised in decision-making. Pan et al. [11] attribute this difficulty partly to the mismatch between probabilistic forecasting approaches and the deterministic decision structures of many emergency management organisations, proposing that AI algorithms can help bridge this gap through rapid urban inundation prediction methods. O'Shea et al. [30] further developed this approach by integrating social narratives of flood events into text network analysis-based decision support frameworks, potentially improving how uncertainty information is processed and used by decision-makers.

Group dynamics introduce additional complexity to flood decision-making processes. Yilmaz [16] identified how multi-stakeholder interactions within fuzzy decision frameworks can either enhance or impede effective flood risk management. The analysis revealed that authority gradients within emergency management teams often suppress dissenting viewpoints that might otherwise identify flawed assumptions. This pattern is particularly evident in cross-jurisdictional flood responses, where institutional hierarchies can create communication barriers [12]. Addressing these social and organisational dimensions is as crucial as improving technical forecasting capabilities. Table 2 provides an overview of the cognitive and psychological factors. To make the table internally consistent, the factors are grouped into four sets according to the cognitive mechanism involved: decision strategies under time pressure; stress and fatigue; risk perception and experience-based judgement; and the interpretation of uncertain information. Only mechanisms that operate within individual decision-makers are included. Where a factor also has a technological or methodological aspect, that aspect is reported in the relevant section under the primary-locus rule (Section 2.3); for example, the way in which forecast systems present uncertainty is discussed under technological factors (Section 3.4).

Table 2. Cognitive and Psychological Dimensions.

Factor	Description
Decision strategies under time pressure	
Naturalistic Decision-Making (NDM)	Experienced responders rely on pattern recognition rather than exhaustive analysis in complex, time-pressured situations [35,36].
Limited Option Consideration	Experienced managers typically evaluate only 2–3 options for critical inputs [24,35].
Stress and fatigue	
Psychological Stress Effects	Acute stress narrows attention and reliance on habitual responses, especially during urban waterlogging [41].
Sleep Deprivation Impact	Extended flood operations degrade decision quality, affecting resource delivery [12].
Decision Error Correlation	Decision errors increase during emergency material distribution in flood disasters, impacting SDG implementation [27].
Risk perception and experience-based judgement	
Risk Perception of Decision-Makers	Responders' and decision-makers' perception of flood risk, shaped by training, organisational norms, prior experience and the presence or absence of risk cues, influences which threats are acted upon and how much personal risk is accepted, for example in decisions to drive through floodwater; individual beliefs also shape which flood-risk measures are selected.
Availability Heuristic	Decision-makers often overweight recent experiences, leading to resource allocation biases [24].
Experience-Based Resource Allocation	Communities with higher exposure to hazards exhibit distinct patterns of resource allocation [22].
Experience-Based Evacuation Decisions	Officials using GIS-AHP techniques make varied evacuation decisions based on prior flood exposure [1].
Interpretation of uncertain information	
Uncertainty Communication Challenges	Few emergency managers systematically integrate complex uncertainty information into decision-making [1].
Probabilistic-to-Deterministic Translation	Decision-makers must convert probabilistic forecasts into deterministic actions, such as whether to order an evacuation, and frequently do so without fully accounting for the forecast uncertainty range [11].

Note: Factors are grouped by the cognitive mechanism involved. Public risk perception is reported among the social and community factors (Table 5, Public Response Determinants), and the presentation of forecast uncertainty by decision-support systems among the technological factors (Section 3.4).

In high-pressure urban flooding contexts, experienced emergency managers primarily employ Naturalistic Decision-Making (NDM), drawing on intuitive pattern recognition rather than detailed analytical methods to navigate time-sensitive crises. This approach naturally leads to Limited Option Consideration, with decision-makers typically evaluating only a few response alternatives rather than exhaustively analysing all possibilities. However, this process becomes progressively compromised by Psychological Stress Effects, which narrow attention and increase reliance on habitual responses, leading to decision errors during periods of highest stress. These challenges are compounded by Sleep Deprivation Impact during extended flood operations, creating dangerous situations where decision quality deteriorates precisely when critical judgments about evacuations or re-

source deployments must be made. Figure 2 presents the integrative overview model that frames the dimension-specific diagrams that follow.

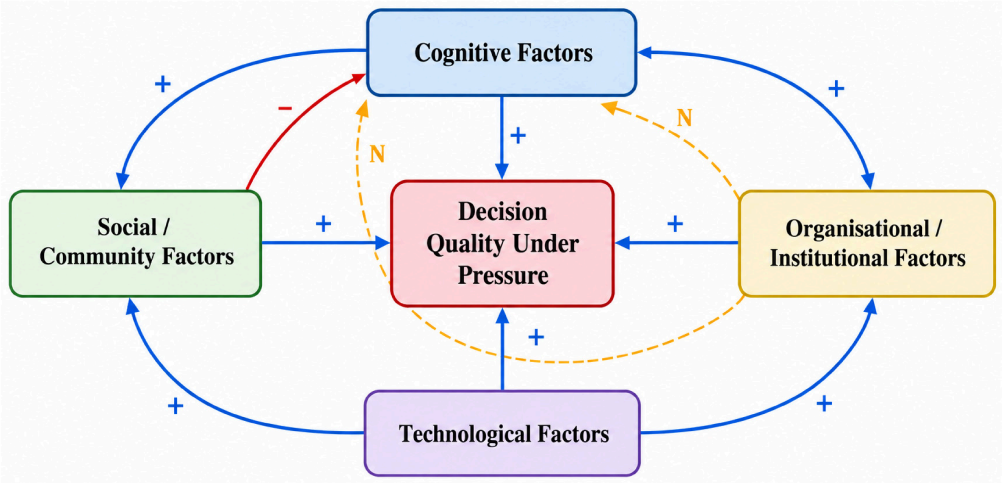

Figure 2. Integrative cross-dimensional overview model linking cognitive/psychological, organisational/institutional, technological and social/community factors to decision quality under pressure. Cognitive sub-factors (Table 2) are aggregated in a single variable; the internal structure of the organisational, technological and social dimensions is modelled in Figures 3–5, and research methods in Figure 6. +, positive link; −, negative link; N, unsigned context-dependent link.

Figure 2 is not a diagram of the cognitive and psychological dimension alone; it has a deliberately wider boundary than Table 2. Because cognitive and psychological mechanisms rarely operate in isolation during flood emergencies, the figure places decision quality under pressure at the centre and represents the cognitive dimension at an aggregated level, together with the three dimensions through which cognitive effects are amplified or buffered: organisational/institutional, technological and social/community factors. Its purpose is to show the cross-dimensional pathways that connect the four dimensions, not the internal structure of any one of them. The cognitive sub-factors listed in Table 2 (for example, psychological stress effects, limited option consideration, the availability heuristic and uncertainty communication challenges) are aggregated in the Cognitive Factors variable, while the internal structures of the organisational, technological and social dimensions are modelled in Figures 3–5, and the methodological approaches in Figure 6. Figure 2 is therefore the top-level model, and Figures 3–6 are nested sub-models whose variables elaborate its four outer nodes. In Figure 2, the positive links represent the associations reported across the corpus between each dimension and decision quality, and the mutual reinforcement among the cognitive, organisational and technological dimensions. The single negative link from social/community factors to cognitive factors represents evidence that public pressure and conflicting community information add to decision-makers' cognitive load. The two unsigned (N) links from organisational/institutional factors to cognitive factors represent context-dependent effects: clear roles and coordination protocols can relieve cognitive load, whereas fragmented authority can add to it. In line with Section 2.4, these unsigned links are not used to determine loop polarity.

3.3. Organisational and Institutional Factors

The fragmented institutional landscape of flood management creates significant coordination challenges. Usón et al. [42] used participatory geographic approaches to map governance structures in Santiago, Chile, identifying multiple distinct agencies with overlapping flood management responsibilities. This complexity creates what Roth et al. [43]

term "watered-down politics," where critical decisions require consensus across multiple organisations with different priorities, information bases, and risk tolerances. Data from major flood events revealed that response delays were significantly longer in regions without pre-established coordination protocols compared to those with integrated command structures [44]. More recently, Wenger et al. [12] demonstrated how these fragmented governance frameworks continue to impede the equitable delivery of flood management benefits, with impacts on marginalised communities.

Information sharing across organisational boundaries remains a challenge, despite technological advances. Sharma et al. [45] documented how information often flows through formal channels too slowly to support rapid decision-making, leading to the emergence of informal communication networks that bypass official structures. Their analysis of event-driven flood management revealed that a substantial proportion of critical information exchanges took place through unofficial channels. Witting et al. [46] observed that following the 2016 Braunsbach flash flood, the impact of scientific scrutiny led to substantial changes in information flow between research institutions and management agencies, but communication with the public remained problematic. Kotzee and Reyers [47] note that differences in professional terminology and data standards between meteorological services, hydrological agencies, and emergency responders frequently lead to information distortion, with technical forecast information often being misinterpreted or lost in translation between issuing agencies and end-users. More recently, Ngo and Do [48] demonstrate how digital transformation initiatives can bridge these communication gaps, though implementation remains challenging in many regions.

Institutional learning from flood events shows mixed effectiveness. Benson et al. [49] evaluated social learning in England's flood risk management system, finding that while technical improvements were consistently implemented, changes to decision processes occurred in only a small percentage of cases despite being frequently recommended in after-action reports. Witting et al. [46] attribute this disparity to the difficulty in creating effective "learning spaces" within existing governance structures. Their evaluation of flood risk management in Germany identified several institutional barriers to implementing lessons learned. On a more positive note, Schinko et al. [50] documented successful cases of institutional learning in Austria, particularly when methodological frameworks were developed to operationalise climate risk management. More recently, Vitale, [51] analysed the shift toward risk-based approaches in flood management across three Italian rivers, revealing significant improvements in institutional capacities when systematic learning processes were established. Simulation can also support institutional learning: Han and Peng [31] used agent-based modelling to show how interactions among local government, residents and insurers shape coastal adaptation outcomes, allowing coordination strategies to be explored before they are tested in a real event. Table 3 provides an overview of the organisational and institutional factors.

Table 3. Summary of organisational and institutional factors identified in the reviewed studies.

Factor	Description
Coordination Impact on Response Time	Response is slower where coordination protocols and integrated command arrangements have not been established in advance [44,52].
Institutional Bottlenecks	Decisions that require consensus among agencies with different priorities and risk tolerances create bottlenecks that delay action [43].

Table 3. *Cont.*

Factor	Description
Institutional Fragmentation	Several agencies frequently hold overlapping flood-management responsibilities within the same urban area, complicating coordination [42].
Informal Information Networks	When formal channels are too slow, critical operational information is often exchanged through informal routes that bypass official structures [45].
Information Distortion	Differences in terminology and data standards between forecasting, hydrological and emergency agencies can cause technical information to be misinterpreted [47].
Implementation Gap	Recommended changes to decision processes are implemented far less consistently after floods than technical improvements [46,49].
Effective Learning Methods	Systematic learning processes and simulation-based exercises strengthen institutional capacity for flood response [51].
Accountability Challenges	Informal networks can accelerate response but weaken accountability when critical decisions are not documented [41].

Multiple agencies with overlapping flood management responsibilities create fragmented institutional environments, significantly impacting urban flood response. This fragmentation generates Institutional Bottlenecks, necessitating consensus among organisations with differing priorities and risk tolerances [53]. The outcome is marked Impact on Coordination, resulting in significant delays for regions lacking established coordination protocols compared to those with integrated command structures. Such structural challenges impair even sound flood management systems during dynamic flood events, particularly in urban settings with multiple coordinating jurisdictions. Central to this model are "Organisational and Institutional Factors," which connect all elements and reflect the formal and informal structures that guide organisational behaviour. "Institutional Fragmentation" is positioned at the top, signifying the division within institutional approaches that challenges coordination [54]. The "Implementation Gap" exemplifies the disconnect between policy formulation and its practical execution, often exacerbated by fragmentation.

The model identifies communication and information-related challenges. "Informal Information Networks" represents unofficial channels through which information flows, sometimes more influential than formal structures. "Information Distortion" illustrates how information becomes altered as it passes through organisational systems. "Coordination Impact on Response Time" represents how coordination challenges directly affect response speed and effectiveness [55]. "Accountability Challenges" reflect difficulties establishing clear responsibility within complex structures. "Effective Learning Methods" represents organisational capacity to learn from experience, though potentially hindered by fragmentation or coordination problems. The structure reveals complex reinforcing relationships creating organisational dysfunction. Institutional fragmentation increases institutional bottlenecks and the implementation gap; bottlenecks slow coordination and response, and coordination delays and information distortion worsen accountability challenges, while the implementation gap weakens the effective learning that would otherwise reduce these delays [38]. The unsigned (N) link between information distortion and effective learning methods denotes a documented but context-dependent relationship: learning can reduce distortion where lessons are implemented, whereas distorted information can also impair learning. The model suggests effective organisational improvement requires understanding and addressing multiple interconnected factors simultaneously. Figure 3 depicts a sys-

tems model highlighting decision-making challenges within organisations and institutions, illustrating the interactions that create complex feedback loops affecting responses.

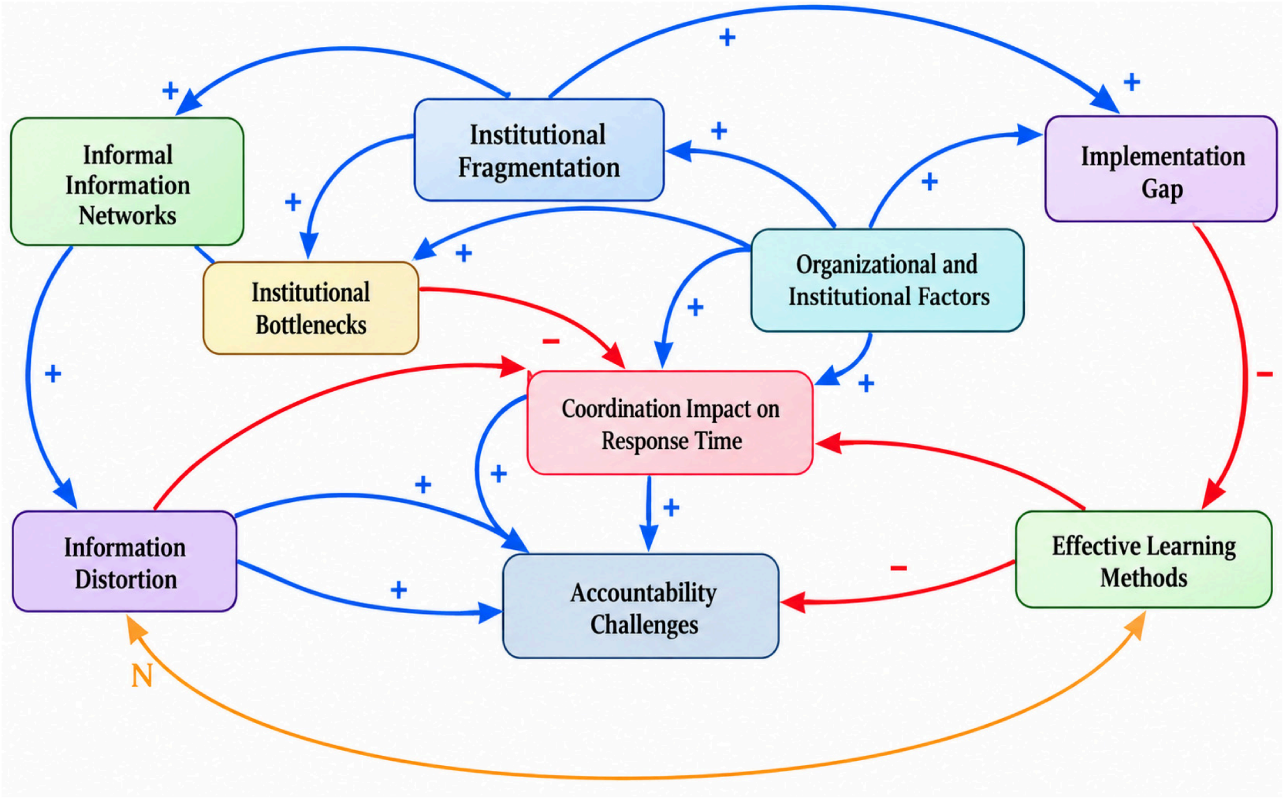

Figure 3. Complex Relationships Among Organisational and Institutional Factors.

3.4. Technological Dimensions and Decision Support Systems

The evolution of flood forecasting and decision support systems reflects a gradual shift from purely technical tools toward more integrated approaches that consider human factors. Espada Jr et al. [56] traced this development in the spatial modelling of disaster risk reduction, noting how early systems focused primarily on improving forecast accuracy without sufficient attention to how the information would be used in decision-making contexts. Their analysis of multiple regional flood management systems revealed that technical sophistication alone was not a reliable predictor of perceived decision utility during actual flood events. More recent approaches have begun incorporating insights from cognitive engineering and human factors research. Gudoshava et al. [57] reported that forecast systems co-produced with end users in Eastern Africa were utilised significantly more frequently during emergencies than technically similar systems designed without stakeholder input. Yazdani et al. [20], further demonstrated that decision support models integrating optimisation and machine learning approaches improved emergency resource allocation efficiency by 34% compared to traditional methods, provided that they were designed with explicit attention to operational decision processes.

Human-technology interaction presents ongoing challenges. Mioc et al. [58] investigated the application of web-based Geographic Information Systems (GIS) to flood risk mapping and emergency evacuation planning, emphasising the importance of accessible, reliable, and user-friendly decision-support tools. Through two case studies in Fredericton, Canada, the researchers demonstrated how near-real-time flood mapping could improve the availability of hazard information, identify vulnerable populations, and support evacuation route planning. Their findings highlighted the importance of designing technological

solutions that accommodate emergency managers' operational requirements while ensuring timely access to relevant information for effective flood response and decision-making. This "regression to technological simplicity" helps explain the persistent gap between available decision technologies and operational practice. Wehn et al. [59] found that participatory approaches incorporating citizen observatories in flood risk management improved information flow but also increased decision complexity. Their governance analysis indicated that systems designed with collaborative visualisation techniques, adapted to operational needs, showed significantly higher utilisation rates during actual emergencies compared to equally accurate but less intuitive systems. Butt et al. [22] further observed that effective adaptation requires balancing technological sophistication with contextual usability, noting that societal perceptions strongly influenced how technical information was interpreted and applied in high-risk situations.

Emerging technologies, including artificial intelligence and real-time analytics, offer new capabilities but introduce additional complexity. Gudoshava et al. [57] observed that application of real-time sub-seasonal to seasonal (S2S) forecasts enhanced predictive capabilities but created interpretation challenges for end users. Their analysis of climate services co-production in Eastern Africa found that many users expressed difficulty in translating probabilistic forecasts into operational decisions. Madhusudhan et al. [1] demonstrated how integrative GIS-AHP techniques could improve flood susceptibility analysis by combining multiple data sources and stakeholder inputs. Still, they cautioned that increased methodological complexity requires careful attention to transparency and interpretability [60]. Table 4 provides an overview of the technological dimensions and decision support systems. This highlights what several researchers identify as the "black box dilemma," where increased predictive power through advanced algorithms comes at the cost of decreased interpretability and, therefore, potentially reduced operational utility.

Table 4. Summary of technological dimensions and decision support systems in the reviewed studies.

Factor	Description
Technological Regression Under Pressure	Under high stress, emergency responders frequently revert to simpler, familiar tools and prioritise reliability over advanced capability [58].
Technical Sophistication	Technical sophistication alone is not a reliable predictor of perceived decision utility; emergency managers often value information on potential and actual damage more highly [56,61].
Visualization Effectiveness	Systems with visualisation adapted to operational needs are used more during emergencies than equally accurate but less intuitive systems [59].
AI Prediction Improvements	AI-based and data-driven prediction methods improve forecast accuracy and speed relative to conventional approaches, although reported gains vary widely between study settings [11,62].
Black Box Dilemma	Emergency managers are reluctant to rely on forecasts or AI outputs whose reasoning they cannot interpret, and favour transparent, risk-based forecasting approaches [63].
Increased Predictive Power and Interpretability	Advanced systems often sacrifice interpretability for predictive capability; frameworks can help mitigate this [56].

The technological landscape of flood emergency management reveals fundamental tension between advancing capabilities and practical usability [64]. Despite substantial investments in Technical Sophistication, flood management systems often show weak correlation between technical complexity and perceived decision utility, explaining Technological Regression Under Pressure, where flood managers frequently prioritise familiar, simpler tools over advanced systems during high-stress periods. This regression effect can be par-

tially mitigated through Visualisation Effectiveness, as systems with visualisation techniques adapted to operational needs demonstrate significantly higher utilisation rates during actual emergencies compared to equally accurate but less intuitive systems [65]. Figure 4 presents a systems model exploring complex relationships within AI and predictive technology systems, focusing on tensions between technological advancement and interpretability challenges. At the centre is "Technological Regression Under Pressure," which represents the point at which technological systems may become less effective under various pressures. "Technical Sophistication" represents complexity and advanced capabilities, while "Visualisation Effectiveness" refers to the ability to represent how complex systems work.

The "Black Box Dilemma" represents fundamental challenges in modern AI systems. As algorithms become more sophisticated, they often become less interpretable. Users may not fully understand how systems arrive at conclusions, creating tension between performance and explainability. The model reveals a critical trade-off: as systems enhance predictive capabilities, they often become less interpretable. This opacity can lead to pressure for transparency, causing systems to regress technologically in ways that diminish effectiveness. Overcoming these cycles requires enhancing both predictive power and interpretability concurrently. A systems perspective underscores the need to recognise the interplay among technical sophistication, visualisation capabilities, and interpretation.

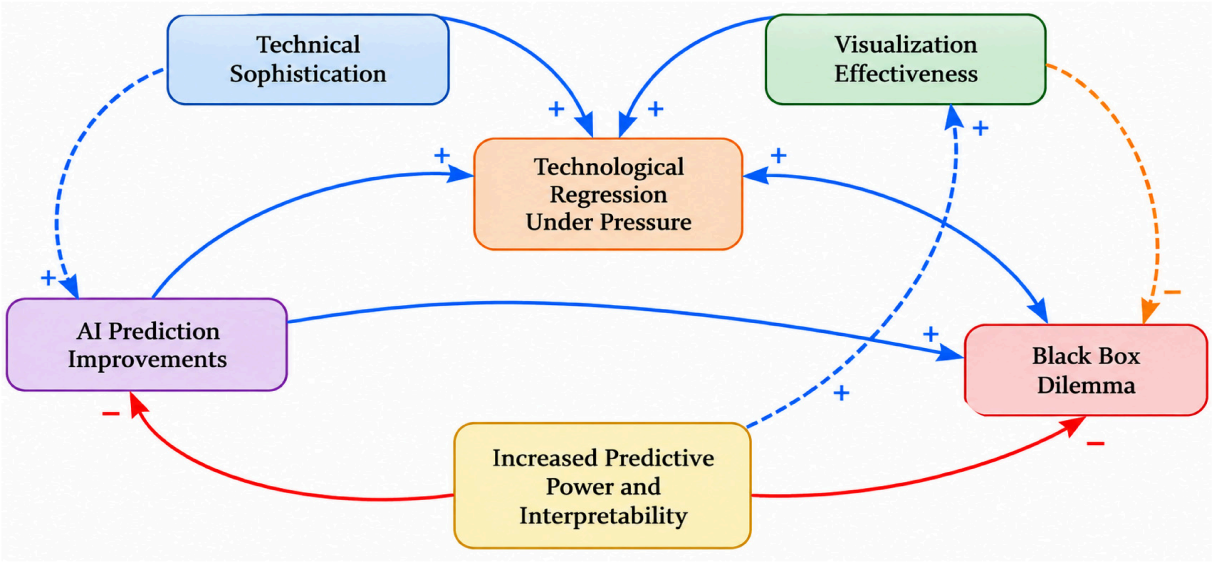

Figure 4. Complex Relationships Among Technological Factors.

3.5. Social and Community Dimensions

Social and community dimensions play a critical role in determining the effectiveness of flood risk management, emergency response, and evacuation decision-making. Public behaviour, risk perception, socioeconomic vulnerability, communication accessibility, and social networks collectively influence how individuals and communities respond to flood warnings and protective measures. Similarly, Eakin et al. [66] investigated mental models and socio-hydrological risk perceptions in Mexico City, demonstrating how collective interpretations of flood hazards influence perceived solutions and response pathways. Harvey et al. [67] examined future flood risks in China's Taihu Basin, providing additional context for understanding flood vulnerability and its potential implications. These disparities stem partly from what Madhuri et al. [68], described as "structural communication barriers," where standard warning protocols fail to reach or resonate with marginalised communities. Phongsapan et al. [69] also demonstrated the application of Earth observation

and cloud computing technologies to operational flood risk index mapping in Myanmar, illustrating how spatial risk information can support disaster risk reduction planning. As summarised in Table 5, non-compliance with evacuation orders was associated with 37% of flood-related fatalities in relocated communities, highlighting the potentially severe consequences of inadequate risk communication and limited public engagement [70]. Understanding the factors' influencing compliance is therefore essential for developing effective and socially responsive flood management strategies.

Table 5. Summary of Social and Community Dimensions.

Factor	Description
Non-Compliance Impact on Fatalities	37% of flood fatalities in relocated communities were attributed to non-compliance with evacuation orders, which was influenced by risk perception [70].
Public Response Determinants	Key factors include trust in authorities (31% variance), risk perception (27%), and prior flood experience (23%), with improved compliance linked to operational emergency response mapping [64].
Tailored Communication Effectiveness	Community-based information systems enhanced evacuation compliance by 28–43% compared to standardised methods, particularly benefiting rural areas [71].
Socioeconomic Disparities	Coastal communities with lower socioeconomic status faced 3.2 times higher flood-related displacement despite similar exposure, revealing notable disparities in recovery [60].
Communication Inequity	Marginalised communities received effective warnings an average of 2.8 h later than majority groups, demonstrating significant timing disparities [72].
Social Capital Recovery Impact	Communities with higher social connectedness recovered from flood damage 1.9 times faster, a significant enhancement facilitated by community-based risk management [60].
Informal Information Channels	43% of urban residents received initial warnings via social networks instead of official channels, highlighting the importance of local information [73].
Adaptive Decision Frameworks	Decision-making that accommodates diverse community needs has boosted response effectiveness by 42%, with stakeholder integration leading to better outcomes [70].

Public response to flood warnings is influenced by several interconnected behavioural and institutional factors. Table 5 identifies trust in authorities (31%), risk perception (27%), and previous flood experience (23%) as important determinants of public response, with the reported percentages representing their respective contributions to explaining behavioural variation [64]. These findings highlight the importance of public confidence, perceived vulnerability, and experiential knowledge in shaping preparedness and evacuation decisions. Jukrkorn et al. [65] further examined community-based flood risk management in Thailand, emphasising the importance of local participation and community engagement. Butt et al. [22] also explored societal perceptions and adaptive responses to glacial lake outburst flood hazards in Pakistan, reinforcing the importance of incorporating community perspectives into flood risk management.

Effective risk communication is another essential component of socially inclusive flood decision-making. Evidence presented in Table 5 indicates that community-based information systems improved evacuation compliance by 28–43% compared with standardised communication approaches, particularly in rural communities [71]. This improvement

highlights the potential value of tailoring warning messages to local knowledge, communication practices, and community characteristics. Nevertheless, communication inequities remain a significant challenge, especially among marginalised and socioeconomically disadvantaged populations. Table 5 reports that vulnerable communities received effective flood warnings approximately 2.8 h later than majority population groups [72]. Such delays may reduce the time available for evacuation, emergency preparation, and other protective actions. Consequently, equitable access to timely, understandable, and actionable warning information should be considered a fundamental requirement of effective flood emergency management.

Socioeconomic inequalities further influence flood exposure, vulnerability, displacement, and recovery. As reported in Table 5, coastal communities with lower socioeconomic status experienced 3.2 times higher flood-related displacement than more advantaged communities despite comparable physical exposure [60]. This disparity indicates that flood consequences cannot be explained solely by the magnitude or geographical distribution of hazards. Differences in financial resources, housing security, access to transportation, institutional support, and recovery capacity may significantly influence individual and community outcomes. These approaches highlight the importance of integrating physical hazard information with social vulnerability considerations when developing inclusive flood decision-support systems.

Social capital and informal information networks also influence community resilience and recovery. According to Table 5, communities characterised by stronger social connectedness recovered from flood-related damage 1.9 times faster than communities with weaker social networks [60]. This finding highlights the potential importance of interpersonal relationships, collective participation, mutual assistance, and local knowledge in supporting post-disaster recovery. Furthermore, 43% of urban residents initially received flood warnings through social networks rather than official communication channels [73]. Although informal networks may facilitate rapid information dissemination, their effectiveness depends on the credibility, accuracy, and accessibility of shared information. Integrating trusted community networks with formal warning systems could therefore strengthen information coverage and improve coordination during emergencies.

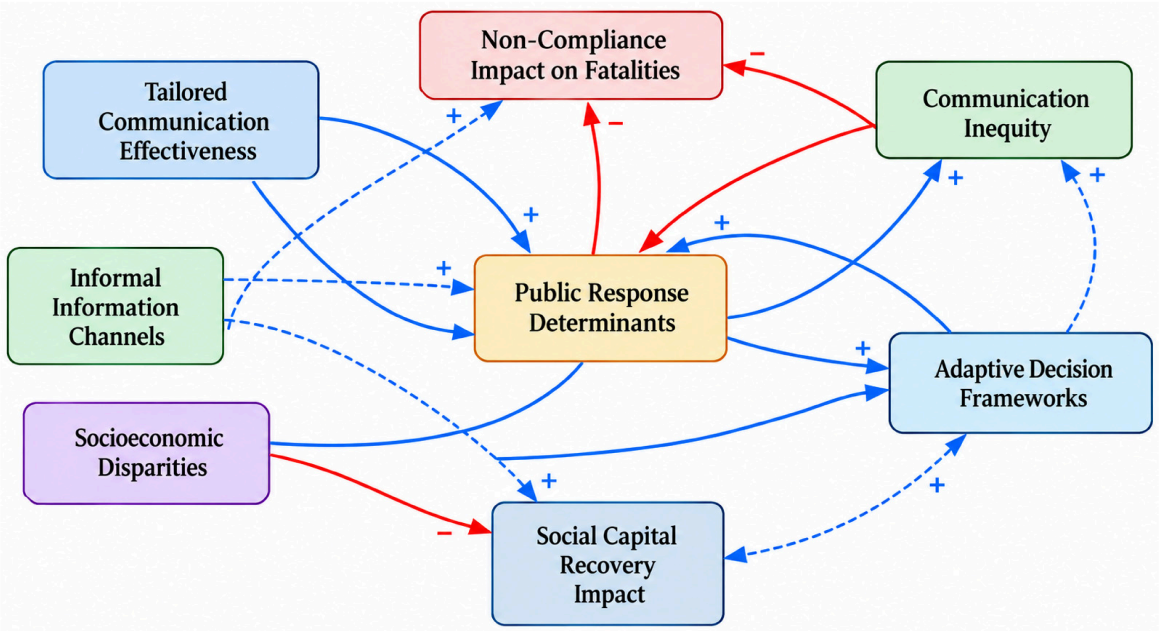

Figure 5. Complex Relationships Among Social and Community Factors.

Adaptive decision-making frameworks provide an additional opportunity to address the diverse needs of flood-affected communities. Decision-making approaches incorporating community-specific requirements and stakeholder participation improved response effectiveness by 42% [70]. This suggests that participatory and context-sensitive decision processes may offer advantages over uniform emergency management approaches, particularly where communities differ in vulnerability, communication access, and institutional capacity. Integrating socioeconomic conditions, behavioural responses, informal information channels, and community resilience into flood decision-support frameworks can therefore help align emergency interventions with local needs and operational realities.

3.6. Methodological Approaches to Studying Flood Decision-Making

Methodological innovation has expanded possibilities for flood decision-making research. Traditional approaches relied heavily on post-event analysis, which Li et al. [74] note is limited by recall bias and difficulty reconstructing decision sequences. Contemporary methods increasingly employ mixed approaches combining multiple data sources. Li et al. [75] evaluated a real-time, satellite-based operational flood prediction system in Africa, illustrating how evaluation during operation can capture how information is used as events unfold rather than reconstructing it afterwards. Mioc et al. [58] demonstrated how combining social vulnerability data with hazard mapping could identify critical gaps in warning protocols invisible to single-method approaches.

Simulation and serious gaming approaches provide controlled environments for studying complex decision processes. Virtual geographic and three-dimensional simulation environments [76] extend this approach by providing immersive representations of flood scenarios that may elicit more realistic responses while maintaining experimental control. Integration of qualitative and quantitative approaches has yielded important insights. Islam et al. [60] combined statistical analysis with community-based risk assessment in coastal Bangladesh, identifying "contextual rationalities" where apparently suboptimal decisions reflected legitimate concerns about social acceptability or resource limitations. Eakin et al. [66] employed mental model analysis alongside socio-hydrological risk assessment in Mexico City, revealing systematic differences between institutional and community perspectives not apparent from outcome data alone. Table 6 provides an overview of methodological approaches to studying flood decision-making.

Table 6. Methodological Approaches.

Factor	Description
Post-Event Analysis Limitations	Traditional methods face recall bias and difficulty reconstructing decisions, while integrated modelling offers a better pre-flood representation [77].
Process Tracing Methods	Direct observation shows significant impacts on flood policy learning, with decision-makers mainly relying on established frameworks [78].
Simulation Exercises	Controlled environments enable systematic variations in factors, with multi-satellite analysis enhancing operational flood management predictions [79].
Non-Linear Time Pressure Effects	Decision quality can decline non-linearly as decision windows shrink; the thresholds at which this occurs are context-specific [80].
Virtual Reality Integration	Immersive and virtual geographic environments enable realistic flood scenarios and vulnerability assessments while maintaining experimental control [81].
Mixed Methods Value	Combining quantitative risk assessment with qualitative analysis reveals decision rationales not visible through single-method approaches [56].

Table 6. *Cont.*

Factor	Description
Hidden Rationalities	Decisions may seem suboptimal yet reflect valid concerns about political acceptability and community impacts, necessitating balanced planning [77].
Cognitive Task Analysis	Mapping mental models revealed systematic differences between institutional and community risk perspectives that were not apparent from outcome data alone [66].

Research into flood emergency decision-making has evolved significantly in response to Post-Event Analysis Limitations, where traditional retrospective studies struggle with recall bias and difficulty reconstructing complex decision sequences. This challenge has driven development of sophisticated approaches, such as Process Tracing Methods, which document decision sequences through direct observation during actual flood events, revealing how decision-makers consult multiple information sources but typically rely on few trusted ones. These insights complement simulation exercises, which create controlled environments for systematically varying conditions like information availability and time pressure. Studies of evacuation decision-making indicate that decision quality can deteriorate non-linearly as the available decision time is compressed [80], although the point at which this occurs is context-specific and has not been established consistently across studies. This controlled manipulation has revealed Nonlinear Time Pressure Effects, where decision quality remains stable until reaching critical thresholds, after which it deteriorates rapidly, although these thresholds are context-specific. The methodological landscape has further expanded through Virtual Reality integration, creating immersive environments that elicit realistic stress responses while maintaining experimental control [82].

Figure 6 displays a systems model examining how different analytical methods interact in complex research environments. At the centre is "Post-Event Analysis Limitations," representing inherent constraints when analysing events retrospectively. The model identifies key analytical approaches: Process Tracing Methods for following event sequences, Cognitive Task Analysis for understanding mental processes, Simulation Exercises for studying behaviour in controlled scenarios, and Virtual Reality Integration for enhancing simulation capabilities [83]. The model includes analytical concepts highlighting decision-making complexity: Hidden Rationalities representing underlying logic driving behaviour, Mixed Methods Value referring to benefits of combining research approaches, and Non-Linear Time Pressure Effects recognising that pressure effects do not follow predictable patterns. Extensive dashed lines suggest relationships are often indirect or uncertain. The model reveals important dynamics: process tracing can enhance cognitive task analysis, though both face post-event analysis constraints. Simulation exercises help overcome some limitations by enabling real-time observation but may not capture real-world complexity [84]. The model reveals tensions in research approaches. While simulation and virtual reality provide controlled environments, they may not fully capture hidden rationalities or nonlinear effects occurring in authentic high-pressure situations [85]. The systems perspective emphasises that effective research requires understanding how methodological approaches complement and constrain each other. Advancing understanding of complex decision-making requires not just better individual methods, but improved integration across multiple analytical approaches.

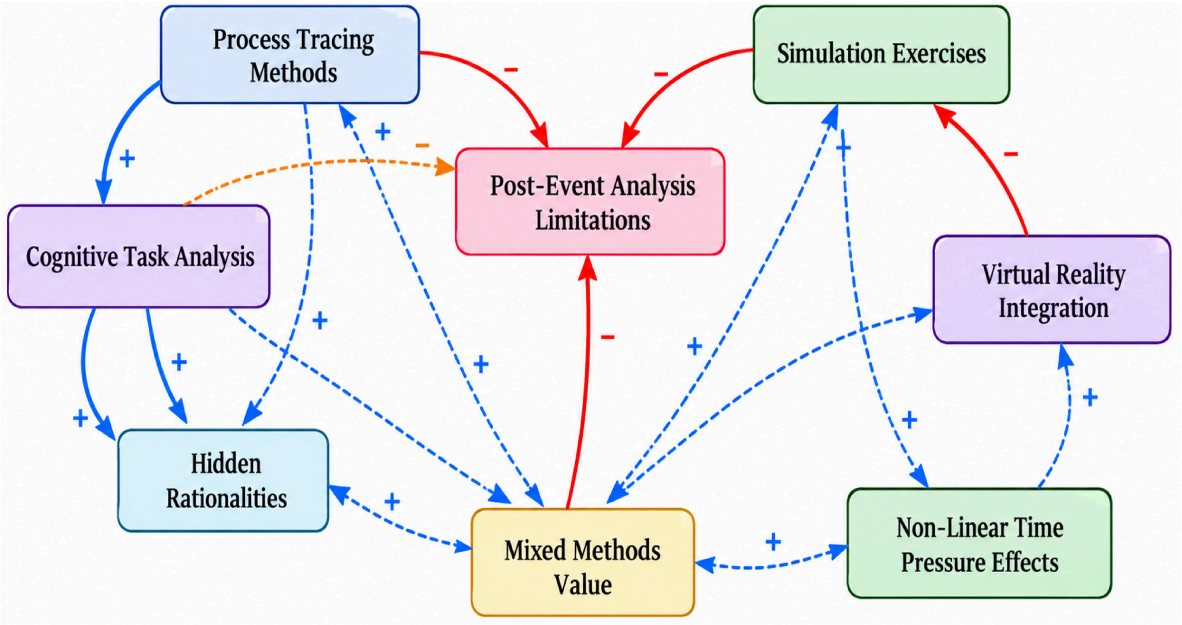

Figure 6. Relationships Among Various Research Methodologies Used to Study Decision-Making in Urban Flood Emergencies.

4. Factors Influencing Decision-Making in Urban Flood Emergencies

Section 4 analyses the 208 included studies published between 2014 and 2026 that reported at least one of ten operational factors (Table 7), in order to trace changes in the prominence and co-occurrence of these factors over time. All of these studies, including those published in 2026, were retrieved by the Scopus search and passed through the complete screening and coding workflow described in Section 2; the 2026 studies reflect publications indexed at the time of the search rather than a complete publication year. For comparison, the coded studies were grouped into three periods: 2014–2017 ($n = 59$), 2018–2021 ($n = 77$) and 2022–2026 ($n = 72$). Across the 2014–2026 subset, policy frameworks and technological tools remained prominent, while later studies increasingly combined governance, real-time data, community participation, risk assessment, and advanced analytics. The field also became more geographically diverse and methodologically interdisciplinary, moving away from single-factor explanations toward integrated decision ecosystems.

The ten operational factors analysed in Section 4 (Risk Assessment, Real-time Data, Communication Systems, Evacuation Planning, Resource Allocation, Infrastructure Management, Policy Frameworks, Community Engagement, Technological Tools, and Historical Data Analysis) correspond exactly to the columns of Table 7 and represent operationalised variables derived from the four thematic dimensions in Section 3. While Section 3 provides a conceptual synthesis of how these dimensions manifest in the literature, Section 4 tracks their relative prominence and co-occurrence across the 2014–2026 corpus to identify evolutionary trends. The factors are not a separate theoretical model but rather a fine-grained decomposition of the broader themes. Other factors discussed in Section 3, such as institutional coordination, leadership and social vulnerability, were analysed qualitatively and were not coded as separate columns.

Table 7. Operational factors coded in the included studies published 2014–2026 ($n = 208$).

Ref. (Year)	Country	Risk Assessment	Real-time Data	Communication Systems	Evacuation Planning	Resource Allocation	Infrastructure Management	Policy Frameworks	Community Engagement	Technological Tools	Historical Data Analysis
[82] (2026)	Iran	✓					✓			✓	
[83] (2026)	USA	✓				✓	✓			✓	
[6] (2026)	Australia	✓	✓							✓	
[84] (2026)	China	✓		✓				✓		✓	
[85] (2026)	China			✓				✓			
[86] (2026)	China			✓				✓			
[4] (2026)	Australia	✓	✓								
[87] (2026)	USA	✓	✓	✓	✓			✓	✓		
[3] (2025)	South Africa	✓		✓		✓		✓	✓	✓	✓
[23] (2025)	China	✓			✓	✓		✓	✓	✓	✓
[21] (2025)	Italy	✓	✓			✓	✓	✓	✓		
[20] (2025)	Australia	✓	✓	✓			✓		✓	✓	
[88] (2025)	China	✓				✓		✓	✓	✓	
[30] (2025)	Zambia	✓				✓		✓	✓		✓
[53] (2025)	China	✓	✓		✓	✓		✓			
[89] (2025)	China		✓		✓	✓		✓		✓	
[12] (2025)	USA	✓				✓		✓	✓		
[25] (2025)	China		✓				✓	✓		✓	
[1] (2024)	India							✓	✓	✓	
[22] (2025)	Pakistan	✓				✓		✓	✓	✓	
[11] (2025)	China		✓					✓		✓	
[24] (2025)	India	✓		✓		✓		✓		✓	
[13] (2025)	China	✓						✓		✓	
[90] (2024)	India							✓		✓	✓
[18] (2025)	China		✓							✓	✓
[38] (2025)	China				✓					✓	✓

Table 7. *Cont.*

Ref. (Year)	Country	Risk Assessment	Real-time Data	Communication Systems	Evacuation Planning	Resource Allocation	Infrastructure Management	Policy Frameworks	Community Engagement	Technological Tools	Historical Data Analysis
[2] (2025)	Philippines									✓	✓
[14] (2025)	China					✓				✓	
[16] (2025)	Turkey							✓	✓	✓	
[91] (2024)	China		✓		✓	✓		✓	✓	✓	✓
[92] (2024)	India	✓				✓	✓	✓		✓	✓
[33] (2024)	USA		✓	✓	✓				✓	✓	
[32] (2024)	UK	✓			✓		✓	✓		✓	
[27] (2024)	China	✓	✓			✓		✓	✓		
[93] (2024)	China		✓			✓	✓	✓		✓	
[94] (2024)	UK		✓		✓		✓	✓		✓	
[95] (2024)	China	✓		✓			✓	✓		✓	
[48] (2024)	Vietnam		✓	✓		✓		✓			
[96] (2024)	India			✓	✓				✓	✓	
[97] (2024)	USA	✓			✓		✓			✓	
[98] (2024)	China	✓				✓		✓		✓	
[10] (2024)	Australia			✓		✓		✓	✓		
[99] (2024)	India		✓	✓				✓		✓	
[100] (2024)	India	✓				✓			✓	✓	
[101] (2024)	Chile		✓				✓	✓		✓	
[102] (2024)	Thailand	✓					✓	✓	✓		
[103] (2024)	Ghana				✓	✓		✓	✓		
[9] (2024)	New Zealand			✓				✓	✓		
[104] (2024)	Jordan	✓					✓			✓	
[105] (2024)	China	✓					✓			✓	
[36] (2024)	Brazil				✓	✓		✓			
[15] (2024)	Canada						✓	✓	✓		

Table 7. *Cont.*

Ref. (Year)	Country	Risk Assessment	Real-time Data	Communication Systems	Evacuation Planning	Resource Allocation	Infrastructure Management	Policy Frameworks	Community Engagement	Technological Tools	Historical Data Analysis
[79] (2024)	China		✓	✓						✓	
[106] (2024)	China					✓	✓		✓		
[107] (2023)	France	✓		✓	✓			✓	✓	✓	
[108] (2023)	China	✓	✓				✓	✓		✓	
[37] (2023)	China		✓				✓	✓		✓	
[109] (2023)	USA					✓	✓	✓	✓		
[110] (2023)	Germany	✓				✓	✓			✓	
[111] (2022)	China		✓					✓	✓	✓	
[112] (2023)	USA				✓	✓		✓	✓		
[113] (2023)	Austria			✓			✓	✓	✓		
[114] (2023)	China					✓		✓	✓		
[115] (2022)	Thailand	✓		✓			✓	✓	✓		
[116] (2022)	Iran	✓		✓		✓		✓	✓	✓	
[117] (2022)	Egypt	✓				✓		✓	✓	✓	
[57] (2022)	Kenya		✓	✓				✓	✓		
[118] (2021)	Taiwan	✓			✓			✓		✓	
[119] (2022)	Switzerland	✓			✓			✓		✓	
[120] (2022)	Vietnam	✓			✓				✓	✓	
[121] (2022)	USA	✓		✓					✓	✓	
[122] (2022)	Peru	✓	✓					✓	✓		
[123] (2022)	China		✓					✓	✓	✓	
[81] (2021)	India	✓					✓	✓	✓	✓	
[54] (2021)	China					✓		✓	✓		✓
[124] (2021)	USA	✓				✓		✓	✓		
[125] (2021)	Iran	✓						✓	✓	✓	
[126] (2021)	Brazil	✓		✓				✓	✓		
[127] (2021)	Turkey	✓							✓	✓	

Table 7. *Cont.*

Ref. (Year)	Country	Risk Assessment	Real-time Data	Communication Systems	Evacuation Planning	Resource Allocation	Infrastructure Management	Policy Frameworks	Community Engagement	Technological Tools	Historical Data Analysis
[128] (2021)	Spain							✓	✓	✓	
[44] (2021)	UK					✓		✓	✓		
[129] (2021)	Italy						✓	✓	✓		
[130] (2021)	Vietnam	✓						✓		✓	
[131] (2021)	Bangladesh							✓	✓	✓	
[132] (2021)	Malaysia					✓		✓			
[133] (2021)	USA			✓						✓	
[134] (2021)	Bangladesh									✓	✓
[135] (2021)	Sweden							✓	✓		
[40] (2021)	Germany							✓	✓		
[136] (2021)	Australia							✓	✓		
[137] (2021)	Netherlands						✓		✓		
[138] (2021)	China		✓					✓			✓
[139] (2020)	India		✓	✓		✓	✓	✓	✓		
[140] (2020)	Mexico				✓	✓	✓	✓	✓	✓	
[141] (2020)	UK	✓						✓	✓	✓	
[41] (2020)	China	✓				✓		✓		✓	
[142] (2020)	Mexico	✓						✓	✓	✓	
[143] (2020)	China	✓				✓		✓	✓		
[144] (2020)	Turkey					✓		✓	✓	✓	
[145] (2020)	UK		✓					✓		✓	
[146] (2020)	UK	✓						✓	✓		
[147] (2020)	Austria				✓			✓	✓		
[39] (2020)	Australia	✓		✓					✓		
[148] (2020)	USA					✓		✓	✓		
[149] (2020)	Greece					✓		✓	✓		
[150] (2020)	China	✓								✓	✓

Table 7. *Cont.*

Ref. (Year)	Country	Risk Assessment	Real-time Data	Communication Systems	Evacuation Planning	Resource Allocation	Infrastructure Management	Policy Frameworks	Community Engagement	Technological Tools	Historical Data Analysis
[151] (2020)	UK							✓		✓	
[152] (2020)	China	✓								✓	
[46] (2020)	Germany							✓	✓		
[153] (2020)	UK							✓	✓		
[154] (2020)	Netherlands					✓	✓				
[155] (2020)	Ireland							✓	✓		
[156] (2019)	Pakistan	✓				✓	✓	✓		✓	
[69] (2019)	Myanmar	✓			✓	✓	✓				
[66] (2019)	Mexico					✓	✓	✓	✓		
[157] (2019)	India	✓						✓	✓	✓	
[158] (2019)	Brazil			✓	✓			✓	✓		
[159] (2019)	Vietnam		✓	✓	✓					✓	
[160] (2019)	Netherlands	✓				✓	✓	✓			
[161] (2019)	China	✓				✓	✓			✓	
[162] (2019)	Austria			✓		✓		✓	✓		
[163] (2019)	Netherlands							✓	✓	✓	
[164] (2019)	Slovenia							✓	✓	✓	
[165] (2019)	UK		✓	✓						✓	
[166] (2019)	Japan	✓				✓				✓	
[167] (2019)	Puerto Rico					✓		✓	✓		
[31] (2019)	USA					✓	✓	✓			
[168] (2019)	China		✓							✓	
[169] (2019)	Kenya							✓	✓		
[170] (2017)	USA					✓		✓	✓		

Table 7. *Cont.*

Ref. (Year)	Country	Risk Assessment	Real-time Data	Communication Systems	Evacuation Planning	Resource Allocation	Infrastructure Management	Policy Frameworks	Community Engagement	Technological Tools	Historical Data Analysis
[171] (2019)	UK								✓	✓	
[172] (2019)	China		✓							✓	
[173] (2018)	China		✓	✓					✓	✓	✓
[174] (2018)	Netherlands		✓	✓		✓			✓		
[175] (2018)	USA	✓		✓					✓	✓	
[176] (2018)	South Africa	✓					✓	✓			
[177] (2018)	France	✓			✓			✓			
[178] (2018)	Malaysia	✓			✓					✓	
[55] (2018)	China					✓		✓		✓	
[179] (2018)	Vietnam							✓	✓	✓	
[180] (2018)	Taiwan			✓					✓	✓	
[181] (2018)	USA	✓							✓	✓	
[182] (2018)	Malaysia	✓	✓								
[183] (2018)	Vietnam								✓	✓	
[184] (2018)	Netherlands					✓		✓			
[185] (2018)	Netherlands								✓	✓	
[186] (2018)	China	✓									✓
[187] (2018)	China								✓	✓	
[188] (2018)	UK								✓		
[189] (2018)	India									✓	
[190] (2017)	South Korea	✓					✓	✓		✓	✓
[191] (2017)	China	✓							✓	✓	✓
[192] (2017)	Sweden		✓	✓					✓	✓	
[193] (2017)	Canada			✓		✓		✓	✓		
[194] (2017)	Nepal			✓				✓	✓		
[195] (2017)	Serbia	✓						✓		✓	
[196] (2017)	Netherlands					✓		✓	✓		

Table 7. *Cont.*

Ref. (Year)	Country	Risk Assessment	Real-time Data	Communication Systems	Evacuation Planning	Resource Allocation	Infrastructure Management	Policy Frameworks	Community Engagement	Technological Tools	Historical Data Analysis
[43] (2017)	Netherlands							✓	✓	✓	
[197] (2017)	USA	✓					✓			✓	
[198] (2017)	Netherlands		✓					✓		✓	
[199] (2017)	UK					✓		✓	✓		
[200] (2017)	China							✓	✓	✓	
[201] (2017)	Brazil	✓	✓							✓	
[202] (2017)	China					✓	✓			✓	
[50] (2017)	Austria	✓						✓		✓	
[203] (2017)	Australia		✓							✓	
[204] (2017)	Germany							✓	✓		
[205] (2017)	China		✓								
[206] (2017)	USA									✓	
[45] (2016)	India		✓	✓		✓		✓		✓	✓
[207] (2016)	USA		✓	✓		✓	✓		✓	✓	
[208] (2016)	Germany			✓				✓	✓	✓	
[42] (2016)	Chile	✓						✓	✓		
[209] (2016)	USA					✓		✓	✓		
[210] (2016)	Australia	✓				✓	✓				
[211] (2016)	Australia			✓				✓		✓	
[47] (2016)	South Africa	✓						✓	✓		
[212] (2016)	Moldova	✓				✓		✓			
[213] (2016)	UK							✓	✓	✓	
[49] (2016)	UK							✓	✓	✓	
[214] (2016)	Saudi Arabia	✓							✓	✓	
[215] (2016)	Austria					✓		✓			
[216] (2016)	Australia	✓								✓	
[217] (2016)	Australia					✓				✓	

Table 7. *Cont.*

Ref. (Year)	Country	Risk Assessment	Real-time Data	Communication Systems	Evacuation Planning	Resource Allocation	Infrastructure Management	Policy Frameworks	Community Engagement	Technological Tools	Historical Data Analysis
[218] (2016)	Austria					✓		✓			
[219] (2016)	EU							✓	✓		
[220] (2016)	Germany								✓		
[221] (2016)	Australia			✓							
[222] (2016)	Germany								✓		
[58] (2015)	Canada	✓	✓	✓	✓	✓			✓	✓	
[223] (2015)	Portugal		✓	✓		✓		✓			
[224] (2015)	USA					✓		✓		✓	✓
[225] (2015)	Italy	✓						✓	✓	✓	
[59] (2015)	Netherlands			✓				✓	✓		
[226] (2015)	Brazil					✓		✓	✓		
[227] (2015)	UK	✓				✓		✓			
[228] (2015)	Netherlands							✓	✓		
[229] (2014)	China	✓	✓			✓	✓	✓		✓	
[230] (2014)	Belgium	✓				✓		✓	✓	✓	
[73] (2014)	China		✓			✓		✓	✓	✓	
[65] (2014)	Thailand				✓			✓	✓	✓	
[56] (2014)	Australia	✓			✓			✓		✓	
[231] (2014)	South Korea	✓					✓	✓		✓	
[70] (2014)	Australia				✓			✓	✓		
[232] (2014)	Italy						✓			✓	
[233] (2014)	Netherlands					✓		✓			
[63] (2014)	UK		✓	✓							
[234] (2014)	Malaysia							✓	✓		

The examination covered ten operational factors shaping flood management across regions and periods. Policy Frameworks (coded in 67% of studies), Technological Tools (58%) and Community Engagement (55%) were the most frequently coded factors overall. Policy Frameworks and Technological Tools remained dominant in every period, and technological tools gained particular prominence in 2022–2026 (67% of studies, compared with 52–54% in the earlier periods) as AI, remote sensing, and computational modelling transformed emergency response capabilities. The research landscape has undergone notable geographic diversification, shifting from predominantly Western-led studies to substantial contributions from Asia, particularly from China. Concurrently, the conceptual approach matured substantially, shifting from compartmentalised examinations of individual factors toward integrated frameworks that acknowledge the complex interplay among governance structures, technological capabilities, community participation, and physical infrastructure.

Increasing integration was assessed directly from the coded matrix by counting the number of operational factors addressed by each study. The mean number of factors per study was 3.1 in 2014–2017 and 3.1 in 2018–2021, but rose to 4.1 in 2022–2026, and the share of studies addressing four or more factors rose from 29% and 32% to 69% (Table 8). Table 7 lists the factors coded for each study, and Table 8 summarises their frequency by period.

Table 8. Frequency of operational factors by publication period (number and percentage of coded studies; derived from Table 7).

Operational Factor	2014–2017 (n = 59)	2018–2021 (n = 77)	2022–2026 (n = 72)	All (n = 208)
Risk Assessment	19 (32%)	28 (36%)	37 (51%)	84 (40%)
Real-time Data	12 (20%)	10 (13%)	25 (35%)	47 (23%)
Communication Systems	12 (20%)	12 (16%)	21 (29%)	45 (22%)
Evacuation Planning	4 (7%)	8 (10%)	17 (24%)	29 (14%)
Resource Allocation	22 (37%)	24 (31%)	29 (40%)	75 (36%)
Infrastructure Management	8 (14%)	13 (17%)	23 (32%)	44 (21%)
Policy Frameworks	40 (68%)	48 (62%)	52 (72%)	140 (67%)
Community Engagement	31 (53%)	47 (61%)	36 (50%)	114 (55%)
Technological Tools	32 (54%)	40 (52%)	48 (67%)	120 (58%)
Historical Data Analysis	4 (7%)	6 (8%)	9 (12%)	19 (9%)
Mean number of factors per study	3.1	3.1	4.1	3.4
Studies addressing four or more factors	29%	32%	69%	44%

The 2014–2026 evidence shows a clear transition from compartmentalised flood-management studies toward integrated decision frameworks. Policy and governance remained consistently important, while technological tools expanded rapidly with AI, remote sensing, real-time monitoring, and predictive analytics. Community engagement retained a stable role, indicating that technological growth has not displaced the need for local knowledge, risk communication, and stakeholder participation. The strongest growth occurred in technology-enabled decision support, but the synthesis also exposes a persistent usability problem: greater predictive capability can increase interpretive burden. This tension is central to the review because emergency value depends on whether information can be understood and acted upon under stress, not on model sophistication alone.

Geographically, the literature diversified from earlier European and North American concentration toward stronger Asian contributions, particularly from China. Conceptually, later studies addressed more factors simultaneously, signalling a shift toward systems thinking and cross-domain explanations of decision quality. Real-time data monitoring (from 20% and 13% of studies in the two earlier periods to 35% in 2022–2026), evacuation planning (from 7% and 10% to 24%) and historical data analysis (from 7% and 8% to 12%)

became more visible in the later literature. The substantive change, however, is not simply the growth of individual factors but their increasing integration: contemporary studies more often connect governance, technology, social vulnerability, and operational response within the same decision framework.

Returning to the three specific objectives stated in the Introduction: Objective 1 (systematic analysis of the interdependence among cognitive, psychological, and institutional factors) is addressed through the causal loop models in Figures 2–6, which map cross-dimensional relationships documented in the corpus. Objective 2 (development of an integrated framework) is achieved through the four-dimension classification schema and its Vensim operationalisation. Objective 3 (identification of critical feedback mechanisms) is met through the reinforcing and balancing feedback structures identified in the causal loop diagrams, most critically the stress-communication-role ambiguity loop and the fragmentation-coordination accountability chain, whose evidence basis is assessed. The review also points to two candidate thresholds that merit empirical testing: the degree of compression of the decision window beyond which decision quality appears to deteriorate non-linearly (Section 3.6), and the level of organisational complexity at which command structures begin to fragment (Section 3.3). Neither threshold could be quantified consistently from the reviewed studies, so both are presented as hypotheses rather than as established values.

5. Discussion

The core synthesis shows that urban-flood decision quality is produced by interactions among cognition, organisational structure, technology, and community context rather than by any single factor. Three findings are especially consistent. First, stress and time pressure narrow attention and reduce the number of options considered. Second, fragmented authority and weak information-sharing amplify delay, ambiguity, and accountability problems. Third, technically advanced decision-support systems lose operational value when interfaces, uncertainty displays, or model outputs exceed users' cognitive capacity.

Recent technology studies also sharpen the distinction between prediction and decision support. Wadhwa et al. [4] demonstrate city-scale GPU-accelerated forecasting for real-time decision-making, while Hossain et al. [6] develop an AIoT-enabled platform for near-real-time flood detection and impact mapping. Jiang et al. [84] use knowledge graphs and fuzzy-enhanced entity recognition to generate flood-control emergency plans, and Fouladi Semnan and Ostad Mirza Tehrani [82] present a cloud-native machine-learning framework for rapid flood-risk mapping. These advances expand speed, scale, and automation, but they do not remove the human-factors problem identified in the core review.

The 2026 literature strengthens rather than overturns these conclusions. Li et al. [85] similarly demonstrate, from an information-consistency perspective, that interdepartmental cooperation is sensitive to the quality and alignment of information shared across emergency-management actors. Together, these studies reinforce the organisational finding that coordination must be designed before and during an event rather than assumed to emerge spontaneously. Liu et al. [86] show that the robustness of urban-flood emergency response networks can be improved through enforced collaboration when stakeholder malfunction disrupts actual response networks.

A particularly important 2026 development is the explicit move toward decision-centred warning systems. Tran et al. [87] argue that flood early-warning systems should treat decision-making as a co-equal component of forecasting, integrating physical science, human behaviour, institutional context, and decision science. This direction is consistent with the present review's central systems insight: information has value only when it is translated into interpretable choices, clear authority, and feasible actions. Sen Gupta et al. [83] likewise

connect calibrated risk estimates to resource-constrained response actions, illustrating the emerging shift from descriptive prediction toward prescriptive analytics.

The 2026 evidence also clarifies what should count as progress in flood decision support. Higher spatial resolution, faster computation, or greater model accuracy are valuable only when they improve the timing, comprehension, or quality of an operational choice. For example, AIoT and GPU-accelerated systems can shorten the interval between observation and forecast, while knowledge graphs can organise dispersed emergency knowledge into structured response options [4–6]. However, these capabilities can still fail at the organisational interface if agencies interpret alerts differently, lack authority to act, or cannot communicate decisions to affected communities. Evaluation should therefore move beyond conventional predictive metrics and include decision latency, user comprehension, trust calibration, coordination performance, fallback reliability, and the equity of warning reach. This broader performance logic directly connects the technological, cognitive, organisational, and social domains identified in the review.

This interpretation also changes how system resilience is understood. Resilience is not simply the ability of a forecasting platform to remain available; it is the ability of the wider decision system to continue producing defensible action when information is incomplete, staff are fatigued, communications are disrupted, and conditions evolve faster than formal procedures. The collaboration results reported by Liu et al. [86] and the information-consistency analysis of Li et al. [85] indicate that redundancy and adaptive coordination are organisational resources, just as backup sensors and communication links are technical resources. Accordingly, flood-response design should pair technological redundancy with role redundancy, cross-trained personnel, alternative communication routes, and pre-authorised decision thresholds. These measures reduce dependence on any single actor or information channel and make the system more tolerant of the failures that are common during severe urban floods.

The cross-domain synthesis therefore identifies three interaction mechanisms. Stress-induced cognitive narrowing becomes more damaging when institutional authority is fragmented because organisational scaffolding cannot compensate for reduced individual capacity. Technology-cognition mismatch occurs when sophisticated tools demand more interpretation precisely when users have less cognitive bandwidth. Social-institutional mismatch occurs when standard warning channels fail to reach or persuade vulnerable groups, producing unequal access to timely protective action. These mechanisms explain why isolated investments in modelling, training, or governance reform can underperform when complementary domains remain weak.

The distinction between flood risk prediction and operational decision-making becomes sharper when urban floods disrupt interdependent infrastructure. Prediction indicates where and when flooding is likely; operational decision-making must determine what to do when the systems that support the response are themselves failing. Rainstorm-induced flooding can cause power outages that disable drainage pumping, which deepens flooding and prolongs outages, producing cascading failures across coupled electricity and drainage networks. Spatio-temporal prediction of power outage risk for interdependent urban electricity and drainage networks under rainstorm disasters [235] provides the kind of infrastructure-state forecast that responders need in order to anticipate where pumping and other critical services will fail. Converting such forecasts into action, however, requires operational optimisation under severe time constraints [236]. These studies indicate that infrastructure-aware decision support should couple risk prediction with tractable operational optimisation, and that human decision-makers will still need interpretable outputs that identify which infrastructure actions are time-critical. This extends the technology–cognition mismatch identified above to the infrastructure domain.

The physical urban context forms a further layer that conditions all three mechanisms, but it is treated only implicitly in much of the reviewed literature. Urban morphology, density and land use determine where floodwater accumulates, how many people and assets are exposed and how quickly access routes and critical services are lost; they therefore shape both the length of the decision window and the set of feasible actions [18,237]. For flood emergency decision-making, this implies that exposure and vulnerability are not fixed inputs but outcomes of morphological choices made long before an event. Dense, mixed-use districts may concentrate exposed populations and complicate evacuation, while also offering shorter distances to shelters and denser informal networks. Decision-support tools and evacuation plans should therefore represent morphology-specific exposure and accessibility explicitly rather than treating the urban area as homogeneous, and future reviews should code urban form as a contextual variable alongside the four dimensions used here.

A further implication concerns uncertainty communication. Flood decisions often require action before forecasts converge, so waiting for certainty can itself become a source of risk. Decision-support systems should therefore distinguish between uncertainty that materially changes the recommended action and uncertainty that does not. This can be achieved through action thresholds, scenario ranges, and explicit statements of what additional information would alter a decision. Such presentation reduces the burden on emergency managers to translate complex probability distributions while preserving transparency about model limitations. It also provides a clearer basis for inter-agency coordination because actors can discuss common action thresholds rather than competing interpretations of technical outputs. In this sense, uncertainty communication is not merely a visualisation problem; it is an organisational design problem linking forecasting, authority, accountability, and public communication. The decision-centred approach emerging in 2026 research supports this shift toward information products that are designed around consequential choices rather than around model outputs alone [87].

Interpretability also depends on how AI-based decision support identifies and presents critical information. Attention mechanisms in deep-learning forecasting models learn to weight the inputs that contribute most to a prediction, such as particular rain gauges, river sensors or time steps, and these weights can be displayed to users as an indication of which observations drove a forecast. For flood emergency decision-making, this offers a route to directing limited attention to the most decision-relevant signals and to reducing the black-box dilemma described in Section 3.4. However, attention weights are not a complete explanation of model reasoning, and their operational value depends on whether they are presented in action-relevant terms and evaluated with emergency managers rather than assumed to improve understanding.

Measurement of cognitive and physiological states is a further underdeveloped area. The review repeatedly invokes stress, fatigue, cognitive load and situational awareness, yet the included studies almost always infer these states from self-reports, retrospective interviews or outcomes rather than measuring them directly. Research in other safety-critical domains shows that physiological signals can be measured and integrated into decisions in real time [238]. Although that study involved a small sample and simplified scenarios, it illustrates how physiological indicators of perceived risk or overload could be used in flood emergency research. In simulation exercises and command-centre training, measures such as fNIRS, heart-rate variability or eye tracking could identify when cognitive load becomes excessive and test whether interface design, task allocation or rest rotations keep decision-makers within a manageable range. Such measurement would allow the stress–decision quality relationships represented in Table 2 and Figure 2 to move from associative to empirically tested links.

5.1. Practical Applications

For emergency-management agencies, the priority is to pre-define decision authority, escalation thresholds, interoperable information formats, and fallback communication channels before flood season. Cross-agency exercises should test these arrangements under realistic time pressure and partial system failure. The 2026 collaboration evidence further supports designing response networks for robustness rather than relying solely on ideal organisational charts. For technology developers, usability under stress should be treated as a core performance criterion alongside forecast accuracy. Decision-support interfaces should minimise unnecessary choice complexity, display uncertainty in action-relevant formats, preserve transparent reasoning where AI is used, and provide graceful fallback modes when data or connectivity degrade. The practical design objective is not maximum sophistication but reliable, interpretable support at the point of decision.

For policymakers and organisational leaders, post-event learning should focus on decision processes as well as technical outcomes. Recommendations should identify why information was delayed, why authority was unclear, why tools were bypassed, and whether vulnerable communities received actionable warnings. Implementation responsibilities and review dates should be assigned so that lessons are converted into institutional change rather than remaining in after-action reports. For training providers, recognition-primed decision-making, stress inoculation, uncertainty interpretation, and inter-agency coordination should be practised together. Scenarios should include compressed decision windows, conflicting information, technology degradation, and community communication challenges. Such exercises better reproduce the coupled conditions revealed by the review than training each competency in isolation.

5.2. Evidence Basis of the Principal Feedback Mechanisms

Table 9 summarises the evidence underlying the principal feedback mechanisms identified in Figures 2–5, using the classification described in Section 2.4. Most individual links are supported by empirical-associative evidence from cross-sectional surveys, case studies and governance analyses, while the effects of stress and time pressure on individual judgement are supported by experimental and naturalistic decision-making research. Evidence collected over time is limited to the learning-related links, where post-event and multi-year studies document how flood experience was, or was not, translated into changes in policy and practice [46,51,78]. None of the closed loops has been observed in full across successive flood events in the included studies. The reinforcing cycles described in Section 3 should therefore be interpreted as theoretically grounded hypotheses about how the documented relationships combine, rather than as empirically established feedback processes. Testing them requires repeated observation of the same organisations or cities across several events, for example through structured after-action data or the monitoring indicators proposed in Section 5.3.

Table 9. Evidence basis of the principal feedback mechanisms.

Mechanism (Principal Links)	Diagram	Evidence Classification	Supporting Studies	Evidence Collected Over Time
Stress and time pressure → narrowed attention and fewer options considered → lower decision quality	Figure 2; Table 2	Empirical-causal for individual links (experimental and naturalistic decision research); empirical-associative in flood settings	[35,80,233]	No; experimental and cross-sectional evidence
Communication breakdown → role ambiguity → reduced situational awareness → further communication breakdown	Figures 2 and 3	Individual links empirical-associative; loop closure conceptual	[45–47]	No

Table 9. *Cont.*

Mechanism (Principal Links)	Diagram	Evidence Classification	Supporting Studies	Evidence Collected Over Time
Institutional fragmentation → bottlenecks → coordination delay → accountability challenges	Figure 3	Empirical-associative (governance analyses and case studies)	[42–44,52]	Limited; comparative case evidence, no repeated measurement
Implementation gap → weaker learning → persistent coordination delay (closure to fragmentation hypothesised)	Figure 3	Learning links empirical-associative; loop closure conceptual	[46,49,51,78]	Partial; post-event and multi-year policy-change studies
Technical sophistication and AI prediction → black-box dilemma → technological regression under pressure	Figure 4	Empirical-associative	[56,58,61,63]	No
Communication inequity → weaker public response → non-compliance → fatalities	Figure 5	Empirical-associative	[58,65,70,200]	No
Social capital → adaptive decision frameworks → recovery	Figure 5	Empirical-associative and conceptual	[60,65,208]	Partial; post-event recovery studies

Note: Evidence classification follows Section 2.4. Loop closure refers to the link that would complete a feedback cycle; no closed loop was observed in full over successive events in the included studies.

5.3. From Feedback Mechanism to Operational Measure: An Illustrative Example

To illustrate how an identified feedback mechanism can be translated into a specific operational measure, consider the fragmentation–coordination–accountability chain in Figure 3. Institutional fragmentation increases institutional bottlenecks; bottlenecks lengthen the time required to coordinate a response; coordination delays and information distortion increase accountability challenges; and the implementation gap weakens the learning that would otherwise reduce these delays in subsequent events. The leverage point is the link between fragmentation and coordination delay: fragmentation itself changes slowly, but its effect on response time can be weakened before an event occurs.

A corresponding operational measure is a pre-agreed, trigger-based joint activation protocol. Before the flood season, the agencies responsible for forecasting, drainage, transport, emergency management and community warning agree on a small set of observable triggers, for example an official heavy-rainfall warning combined with a forecast or observed exceedance of drainage-capacity or water-level thresholds at named locations. When a trigger is met, a unified incident structure is activated automatically, without a further inter-agency consensus decision. Each agency's role, the lead decision-maker for evacuation and road closures, the shared operational picture to be used and the fallback communication channel are specified in advance, and every decision taken under the protocol is recorded with its time, decision-maker and information basis in a shared decision log.

Each element of the protocol acts on a specific link in the chain. Pre-agreed triggers and roles remove the need for real-time consensus and so weaken the fragmentation → bottleneck → coordination-delay pathway; the shared operational picture reduces information distortion; and the decision log reduces accountability challenges by documenting decisions that would otherwise be made informally. The log also provides the evidence base for a structured post-event review in which named owners and deadlines are assigned to process changes, narrowing the implementation gap and strengthening the learning link. The effect of the measure can be monitored with indicators that correspond to variables in the diagram: the time from trigger to joint activation, the time from warning to first protective decision, the proportion of key decisions documented, and the proportion of post-event process recommendations implemented by the agreed deadline. Because the closing links of this loop are supported mainly by case-study and conceptual evidence

(Table 9), the same indicators would also generate the longitudinal data needed to test the loop empirically across successive flood events.

5.4. Theoretical and Research Implications

The findings extend naturalistic decision-making and high-reliability organisation perspectives by showing that cognitive adaptation and organisational reliability are interdependent during urban floods. Future research should prioritise longitudinal designs that can establish whether the hypothesised feedback loops close in practice (Table 9), test these cross-domain mechanisms prospectively during exercises and real events, compare human-centred and prediction-centred decision-support designs, and evaluate whether explainable and prescriptive AI improves action quality rather than only predictive performance. The 2026 literature indicates that the field is already moving toward these integrated questions, but comparative evidence on real-world adoption, trust, equity, and institutional learning remains limited. Table 10 summarises the principal findings and their operational implications.

Table 10. Summary of Principal Findings and Operational Implications.

No	Key Finding	Domain	Operational Implication
1	Decision-makers often narrow the option set under stress.	Cognitive	Use recognition-primed training and reduce unnecessary choice complexity in SOPs.
2	Users often revert to simpler, familiar tools under pressure.	Technological	Prioritise robust simplicity, familiarity, and fallback modes in DSS design.
3	Communication breakdowns amplify role ambiguity and reduce situational awareness.	Organisational	Pre-define authority, interoperable information formats, and fallback communication channels.
4	Institutional fragmentation delays coordination and weakens accountability.	Organisational	Stress-test cross-agency command arrangements before flood season.
5	Standard warning channels can underserve marginalised communities.	Social	Use community-specific, redundant and accessible warning channels.
6	Time pressure and prolonged operations degrade decision quality.	Cognitive	Use decision checkpoints, fatigue management, and time-compressed training.
7	AI can improve prediction while increasing interpretability and trust challenges	Technological	Co-design tools with users and require explainability appropriate to operational decisions
8	Post-event technical learning often outpaces decision-process reform	Organisational	Assign ownership, deadlines, and follow-up audits to process recommendations

6. Conclusions

This review integrates cognitive, psychological, organisational, technological, and social evidence on decision-making in urban flood emergencies. The review corpus, identified and screened in accordance with PRISMA 2020, comprises 230 Scopus-indexed studies published between 2009 and 2026. The synthesis shows that response quality depends less on technical capability in isolation than on the fit between information, human cognitive capacity, institutional coordination, and community context. Three cross-domain mechanisms are central: stress can compound fragmented authority; sophisticated technology can become less useful when cognitive demands rise; and formal warning systems can reproduce inequity when institutional communication does not match community needs. Recent 2026 research on emergency-response networks, interdepartmental cooperation, AIoT, knowl-

edge graphs, real-time forecasting, and decision-centred warning systems reinforces the importance of these interactions and shows that the field is moving from prediction-centred tools toward integrated decision support.

For practice, the findings support pre-defined cross-agency authority, interoperable communication protocols, stress-tested and interpretable decision-support tools, structured process-focused learning after events, and training that combines cognitive, technological, and organisational challenges. These priorities translate the review from thematic description into actionable guidance while preserving a systems perspective. The study is limited by its reliance on a single database and on English-language publications; by its partial coverage of 2026, which reflects publications indexed at the time of the search; by the small number of studies underlying some context-specific factors in Tables 2–6; and by the qualitative nature of the causal loop diagrams, whose links are derived from heterogeneous studies and whose closed feedback loops are supported mainly by associative and conceptual rather than longitudinal evidence. Future updates should extend the search to additional databases, and future empirical work should test the principal feedback mechanisms prospectively during exercises and real flood operations, including through direct measurement of decision-makers' cognitive and physiological states and explicit representation of urban morphology and infrastructure interdependencies.

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References

1. Madhusudhan, R.; Bhavani, G.; Avinash, G.; Sushmanth, J.; Sri, R.; Praveen, S. Integrative GIS-AHP Techniques for Flood Susceptibility Analysis in Nashik, Maharashtra. *Disaster Adv.* **2024**, *18*, 24–37. [CrossRef]
2. Besarra, I.; Opdyke, A.; Mendoza, J.E.; Delmendo, P.A.; Santiago, J.; Evangelista, D.J.; Lagmay, A.M.F.A. The cost of flooding on housing under climate change in the Philippines: Examining projected damage at the local scale. *J. Environ. Manag.* **2025**, *380*, 124966. [CrossRef] [PubMed]
3. Sibandze, P.; Kalumba, A.M.; Aljaddani, A.H.; Zhou, L.; Afuye, G.A. Geospatial mapping and meteorological flood risk assessment: A global research trend analysis. *Environ. Manag.* **2025**, *75*, 137–154. [CrossRef] [PubMed]
4. Wadhwa, A.; Sharma, A.; Xia, X.; Chan, T.P.; Kumar, K.; Kumar, D.N.; Dodd, C.; Kuetemeyer, C. GPU-accelerated city-scale urban flood forecasting for real-time decision-making. *npj Nat. Hazards* **2026**, *3*, 31. [CrossRef]
5. Wang, H.; Liu, S.; Li, L.; Zuo, J.; Meng, X.; Goodsite, M.; Jiao, L.; Wu, L. Dynamic evolutionary pathway analysis of urban rail transit flood risks and intelligent decision support based on knowledge graphs. *Reliab. Eng. Syst. Saf.* **2026**, *273*, 112345. [CrossRef]
6. Hossain, S.T.; Yigitcanlar, T.; Lin, Z.; Zhao, P. AIoT-enabled urban platform for flood detection and impact mapping: Towards near-real-time spatial decision support in disaster management. *Nat. Hazards* **2026**, *122*, 621. [CrossRef]

7. Bovermann, Z.E.; Dietrich, J.; Koessler, A.-K. Impact-based decision making in flood risk management: A review of behavioral and technical approaches. *Int. J. Disaster Risk Sci.* **2026**, *17*, 240–252. [CrossRef]
8. Piaseckienė, G.; Antuchevičienė, J. Urban flood disaster risk management using multi-criteria decision-making methods: A scoping review. *Int. J. Strateg. Prop. Manag.* **2025**, *29*, 449–468. [CrossRef]
9. Bajestani, S.A.; Serrao-Neumann, S.; Hanna, C.; Fu, X. Dealing with uncertainty in flood risk management and land use planning decisions: Insights from Aotearoa New Zealand. *Clim. Risk Manag.* **2024**, *46*, 100666. [CrossRef]
10. Semnan, A.F.; Maqsood, T.; Venkatesan, S. Investigating the influence of information sources on flood-coping appraisal: Insights into flood mitigation behaviour. *Int. J. Disaster Risk Reduct.* **2024**, *113*, 104865. [CrossRef]
11. Pan, X.; Hou, J.; Chen, G.; Li, D.; Zhou, N.; Imran, M.; Li, X.; Qiao, J.; Gao, X. Rapid urban inundation prediction method based on numerical simulation and AI algorithm. *J. Hydrol.* **2025**, *647*, 132334. [CrossRef]
12. Wenger, S.J.; Bhaskar, A.S.; Murphy, B.; Neale, M.; Scoggins, M.; Barrett, I.; Bledsoe, B.; Capps, K.A.; Castillo, M.M.; Pascacio, E.D.; et al. Reorienting urban stream management to focus on equitable delivery of benefits. *PLoS Water* **2025**, *4*, e0000308. [CrossRef]
13. Xie, Z.; Shu, B. Risk Assessment and Spatial Zoning of Rainstorm and Flood Hazards in Mountainous Cities Using the Random Forest Algorithm and the SCS Model. *Land* **2025**, *14*, 453. [CrossRef]
14. Du, W.; Liu, C.; Xia, Q.; Wen, M.; Hu, Y.; Chen, Z.; Xu, L.; Zhang, X.; Terfa, B.K.; Chen, N. OFPO & KGFPO: Ontology and knowledge graph for flood process observation. *Environ. Model. Softw.* **2025**, *185*, 106317. [CrossRef]
15. Cottar, S.; Wandel, J. Municipal perspectives on managed retreat and flood mitigation: A case analysis of Merritt, Canada after the 2021 British Columbia flood disaster. *Clim. Change* **2024**, *177*, 50. [CrossRef]
16. Yilmaz, M.U. Enhancing sustainable flood risk management through a novel fuzzy multi-stakeholder framework. *Water Resour. Manag.* **2025**, *39*, 1453–1480. [CrossRef]
17. Abbas, R.; Miller, T. Exploring communication inefficiencies in disaster response: Perspectives of emergency managers and health professionals. *Int. J. Disaster Risk Reduct.* **2025**, *120*, 105393. [CrossRef]
18. Zhou, J.; Zhang, S.; Wang, H.; Ding, Y. Spatial Coupling Analysis of Urban Waterlogging Depth and Value Based on Land Use: Case Study of Beijing. *Water* **2025**, *17*, 529. [CrossRef]
19. Semnan, A.F.; Maqsood, T.; Venkatesan, S. Applying Machine Learning Techniques to Identify Key Factors Motivating Flood-Prone Residents to Implement Private Flood Mitigation Measures. *Nat. Hazards Rev.* **2024**, *25*, 4024026. [CrossRef]
20. Yazdani, M.; Shahriari, S.; Haghani, M. Real-time decision support model for logistics of emergency patient transfers from hospitals via an integrated optimisation and machine learning approach. *Prog. Disaster Sci.* **2025**, *25*, 100397. [CrossRef]
21. Ugliotti, F.M.; Daud, M.; Iacono, E. Spatial Insights for Building Resilience: The Territorial Risk Management & Analysis Across Scale Framework for Bridging Scales in Multi-Hazard Assessment. *Smart Cities* **2025**, *8*, 27. [CrossRef]
22. Butt, A.Q.; Shangguan, D.; Banerjee, A.; Farooq, R.; Wang, R.; Afzal, M.; Li, D.; Wang, M.; Wu, J.; Han, T.; et al. Assessing societal perceptions and adaptive responses to GLOF and related hazards in the upper Indus Basin, Pakistan. *Discov. Appl. Sci.* **2025**, *7*, 152. [CrossRef]
23. Shu, X.; Ye, C.; Xu, Z. An Uncertainty Analysis of Low-Impact Development Based on the Hydrological Process with Invariant Parameters and Equivalent Effects: Supporting Sustainable Urban Planning. *Sustainability* **2025**, *17*, 2587. [CrossRef]
24. Parmar, J.; Mohanty, M.P.; Karmakar, S. Need for judicious selection of runoff inputs in a global flood model. *Environ. Res. Lett.* **2025**, *20*, 24032. [CrossRef]
25. Zhao, Z.; Liang, Y.; Wang, K.; Ding, X.; Zhang, Y.; Hu, C. Collaborative sensing optimization layout model of heterogeneous sensors under urban flooding environment. *J. Hydrol.* **2025**, *650*, 132528. [CrossRef]
26. United Nations General Assembly. *Transforming Our World: The 2030 Agenda for Sustainable Development*; Resolution A/RES/70/1; United Nations: New York, NY, USA, 2015.
27. Li, W.; Jiang, R.; Wu, H.; Xie, J.; Zhao, Y.; Li, F.; Lu, X. A new two-stage emergency material distribution framework for urban rainstorm and flood disasters to promote the SDGs. *Sustain. Cities Soc.* **2024**, *112*, 105645. [CrossRef]
28. Rawat, R.S.; Rawat, V.R.S. Climate Change and Forest Sector in India. In *Textbook of Forest Science*; Springer: Berlin/Heidelberg, Germany, 2025; pp. 253–285.
29. United Nations Office for Disaster Risk Reduction (UNISDR). *Sendai Framework for Disaster Risk Reduction 2015–2030*; UNISDR: Geneva, Switzerland, 2015.
30. O'shea, T.E.; Grobusch, L.C.; Zhang, M.; Neal, J.; Daron, J.; Jones, R.G.; Jack, C.; McClure, A.; Siame, G.; Ndhlovu, D.; et al. Integrating social narratives of flood events into a text network analysis-based decision support framework to reduce vulnerability to climate change in Africa. *Clim. Serv.* **2025**, *37*, 100538. [CrossRef]
31. Han, Y.; Peng, Z. The integration of local government, residents, and insurance in coastal adaptation: An agent-based modeling approach. *Comput. Environ. Urban Syst.* **2019**, *76*, 69–79. [CrossRef]
32. Qin, H.; Liang, Q.; Chen, H.; De Silva, V. A two-way coupled CHANS model for flood emergency management, with a focus on temporary flood defences. *Environ. Model. Softw.* **2024**, *181*, 106166. [CrossRef]

33. Hillin, J.; Alizadeh, B.; Li, D.; Thompson, C.M.; Meyer, M.A.; Zhang, Z.; Behzadan, A.H. Designing user-centered decision support systems for climate disasters: What information do communities and rescue responders need during floods? *J. Emerg. Manag.* **2024**, *22*, 71–85. [CrossRef] [PubMed]
34. Bajestani, S.A.; Stupples, P.; Chanse, V. The changing dynamics of the creative city: Toward an inclusive, participatory, and place-based cultural policy in Wellington, New Zealand. *J. Urban Aff.* **2024**, *47*, 3511–3536. [CrossRef]
35. Klein, G. Naturalistic decision making. *Hum. Factors* **2008**, *50*, 456–460. [CrossRef] [PubMed]
36. de Albuquerque, N.L.B.; da Silva, L.B.L.; Alencar, M.H.; de Almeida, A.T. A multicriteria decision model to improve emergency preparedness: Locating-allocating urban shelters against floods. *Int. J. Disaster Risk Reduct.* **2024**, *111*, 104695. [CrossRef]
37. Zhang, Y.; Shang, K. Cloud model assessment of urban flood resilience based on PSR model and game theory. *Int. J. Disaster Risk Reduct.* **2023**, *97*, 104050. [CrossRef]
38. Huang, H.; Li, X.; He, J.; Liu, H. Analysis and application research on spatiotemporal characteristics of microblog information for rainstorm flood disasters emergency rescue based on text classification. *Int. J. Disaster Risk Reduct.* **2025**, *117*, 105085. [CrossRef]
39. Ahmed, M.A.; Haynes, K.; Tofa, M.; Hope, G.; Taylor, M. Duty or safety? Exploring emergency service personnel's perceptions of risk and decision-making when driving through floodwater. *Prog. Disaster Sci.* **2020**, *5*, 100068. [CrossRef]
40. Brillinger, M.; Henze, J.; Albert, C.; Schwarze, R. Integrating nature-based solutions in flood risk management plans: A matter of individual beliefs? *Sci. Total Environ.* **2021**, *795*, 148896. [CrossRef] [PubMed]
41. Zhou, Y.; Wang, J.; Grigorieva, E.; Egidarev, E.; Zhang, W. Comprehensive Spatio-Temporal Analysis of Travel Climate Comfort Degree and Rainstorm-Flood Disaster Risk in the China–Russia Border Region. *Sustainability* **2020**, *12*, 3254. [CrossRef]
42. Usón, T.J.; Klonner, C.; Höfle, B. Using participatory geographic approaches for urban flood risk in Santiago de Chile: Insights from a governance analysis. *Environ. Sci. Policy* **2016**, *66*, 62–72. [CrossRef]
43. Roth, D.; Vink, M.; Warner, J.; Winnubst, M. Watered-down politics? Inclusive water governance in the Netherlands. *Ocean Coast. Manag.* **2017**, *150*, 51–61. [CrossRef]
44. McGinlay, J.; Jones, N.; Clark, J.; Maguire-Rajpaul, V.A. Retreating coastline, retreating government? Managing sea level rise in an age of austerity. *Ocean Coast. Manag.* **2021**, *204*, 105458. [CrossRef]
45. Sharma, V.K.; Rao, G.S.; Amminedu, E.; Nagamani, P.V.; Shukla, A.; Rao, K.R.M.; Bhanumurthy, V. Event-driven flood management: Design and computational modules. *Geo-Spat. Inf. Sci.* **2016**, *19*, 39–55. [CrossRef]
46. Witting, A.; Brandenstein, F.; Zarfl, C.; Lucía, A. Impact of Scientific Scrutiny after the 2016 Braunsbach Flash Flood on Flood-Risk Management in the State of Baden-Württemberg, Germany. *Water* **2020**, *12*, 1165. [CrossRef]
47. Kotzee, I.; Reyers, B. Piloting a social-ecological index for measuring flood resilience: A composite index approach. *Ecol. Indic.* **2016**, *60*, 45–53. [CrossRef]
48. Ngo, H.V.; Do, H. Flood Risk Management Through Digital Transformation in Connection with Smart Urban Development Management: A Case of Lao Cai City of Vietnam. *Int. J. Sustain. Constr. Eng. Technol.* **2024**, *15*, 40–49. [CrossRef]
49. Benson, D.; Lorenzoni, I.; Cook, H. Evaluating social learning in England flood risk management: An 'individual-community interaction' perspective. *Environ. Sci. Policy* **2016**, *55*, 326–334. [CrossRef]
50. Schinko, T.; Mechler, R.; Hochrainer-Stigler, S. A methodological framework to operationalize climate risk management: Managing sovereign climate-related extreme event risk in Austria. *Mitig. Adapt. Strateg. Glob. Change* **2017**, *22*, 1063–1086. [CrossRef] [PubMed]
51. Vitale, C. Understanding the shift toward a risk-based approach in flood risk management, a comparative case study of three Italian rivers. *Environ. Sci. Policy* **2023**, *146*, 13–23. [CrossRef]
52. Latham, Z.; Barrett-Lennard, G.; Opdyke, A. Archetypes of local governance for flood risk reduction decision-making under uncertain climate change futures. *Sustain. Cities Soc.* **2024**, *112*, 105632. [CrossRef]
53. Gong, Z.; Wang, L.; Yang, J.; Wang, Y.; Zhang, L. Urban Flood Risk Assessment and Optimization of Shelter Site Selection Following a Pre-Expropriation System. *Nat. Hazards Rev.* **2025**, *26*, 4025013. [CrossRef]
54. Shen, J.; Li, S.; Liu, L.; Liang, Z.; Wang, Y.; Wang, H.; Wu, S. Uncovering the relationships between ecosystem services and social-ecological drivers at different spatial scales in the Beijing-Tianjin-Hebei region. *J. Clean. Prod.* **2021**, *290*, 125193. [CrossRef]
55. Chen, P.; Zhang, J.; Sun, Y. Research on emergency rescue of urban flood disaster based on wargame simulation. *J. Indian Soc. Remote Sens.* **2018**, *46*, 1677–1687. [CrossRef]
56. Espada, R., Jr.; Apan, A.; McDougall, K. Spatial modelling of natural disaster risk reduction policies with Markov decision processes. *Appl. Geogr.* **2014**, *53*, 284–298. [CrossRef]
57. Gudoshava, M.; Wanzala, M.; Thompson, E.; Mwesigwa, J.; Endris, H.S.; Segele, Z.; Hirons, L.; Kipkogei, O.; Mumbua, C.; Njoka, W.; et al. Application of real time S2S forecasts over Eastern Africa in the co-production of climate services. *Clim. Serv.* **2022**, *27*, 100319. [CrossRef]
58. Mioc, D.; Nkhwanana, J.; Moreiri, K.; Nickerson, B.; Santos, M.; McGillivray, E.; Morton, A.; Anton, F.; Ahmad, A.; Mezouaghi, M.; et al. Natural and man-made flood risk mapping and warning for socially vulnerable populations. *Int. J. Saf. Secur. Eng.* **2015**, *5*, 183–202. [CrossRef]

59. Wehn, U.; Rusca, M.; Evers, J.; Lanfranchi, V. Participation in flood risk management and the potential of citizen observatories: A governance analysis. *Environ. Sci. Policy* **2015**, *48*, 225–236. [CrossRef]
60. Islam, M.N.; Malak, M.A.; Islam, M.N. Community-based disaster risk and vulnerability models of a coastal municipality in Bangladesh. *Nat. Hazards* **2013**, *69*, 2083–2103. [CrossRef]
61. Molinari, D.; Ballio, F.; Menoni, S. Floods emergency management: The value of potential and actual damage estimation. *WIT Trans. Ecol. Environ.* **2012**, *159*, 95–105. [CrossRef]
62. Byaruhanga, N.; Kibirige, D.; Gokool, S.; Mkhonta, G. Evolution of flood prediction and forecasting models for flood early warning systems: A scoping review. *Water* **2024**, *16*, 1763. [CrossRef]
63. Dale, M.; Wicks, J.; Mylne, K.; Pappenberger, F.; Laeger, S.; Taylor, S. Probabilistic flood forecasting and decision-making: An innovative risk-based approach. *Nat. Hazards* **2014**, *70*, 159–172. [CrossRef]
64. Osti, R.; Miyake, K.; Terakawa, A. Application and operational procedure for formulating guidelines on flood emergency response mapping for public use. *J. Flood Risk Manag.* **2009**, *2*, 293–305. [CrossRef]
65. Jukrkorn, N.; Sachdev, H.; Panya, O. Community-based flood risk management: Lessons learned from the 2011 flood in central Thailand. *WIT Trans. Ecol. Environ.* **2014**, *184*, 75–86. [CrossRef]
66. Eakin, H.; Siqueiros-García, J.M.; Hernández-Aguilar, B.; Shelton, R.; Bojórquez-Tapia, L.A. Mental models, meta-narratives, and solution pathways associated with socio-hydrological risk and response in Mexico City. *Front. Sustain. Cities* **2019**, *1*, 4. [CrossRef]
67. Harvey, G.L.; Thorne, C.R.; Cheng, X.; Evans, E.P.; Simm, S.H.J.D.; Wang, Y. Qualitative analysis of future flood risk in the Taihu Basin, China. *J. Flood Risk Manag.* **2009**, *2*, 85–100. [CrossRef]
68. Madhuri, R.; Raja, Y.S.L.S.; Raju, K.S.; Punith, B.S.; Manoj, K. Urban flood risk analysis of buildings using HEC-RAS 2D in climate change framework. *H2Open J.* **2021**, *4*, 262–275. [CrossRef]
69. Phongsapan, K.; Chishtie, F.; Poortinga, A.; Bhandari, B.; Meechaiya, C.; Kunlamai, T.; Aung, K.S.; Saah, D.; Anderson, E.; Markert, K.; et al. Operational flood risk index mapping for disaster risk reduction using earth observations and cloud computing technologies: A case study on Myanmar. *Front. Environ. Sci.* **2019**, *7*, 191. [CrossRef]
70. Sipe, N.; Vella, K. Relocating a flood-affected community: Good planning or good politics? *J. Am. Plan. Assoc.* **2014**, *80*, 400–412. [CrossRef]
71. Tanaka, K.; Yamada, F.; Kakimoto, R.; Matsuo, K.; Ohmoto, T. Information support systems for community-based flood risk management. *J. Flood Risk Manag.* **2011**, *4*, 156–164. [CrossRef]
72. Tall, A.; Mason, S.J.; van Aalst, M.; Suarez, P.; Ait-Chellouche, Y.; Diallo, A.A.; Braman, L. Using seasonal climate forecasts to guide disaster management: The Red Cross experience during the 2008 West Africa floods. *Int. J. Geophys.* **2012**, *2012*, 986016. [CrossRef]
73. Deng, X.J.; Xu, Y.P.; Zhai, L.X.; Liu, Y.; Li, Y. Establishment and application of the index system for urban river health assessment. *Acta Ecol. Sin.* **2014**, *34*, 993–1001. [CrossRef]
74. Li, K.; Wu, S.; Dai, E.; Xu, Z. Flood loss analysis and quantitative risk assessment in China. *Nat. Hazards* **2012**, *63*, 737–760. [CrossRef]
75. Li, L.; Hong, Y.; Wang, J.; Adler, R.F.; Policelli, F.S.; Habib, S.; Irwn, D.; Korme, T.; Okello, L. Evaluation of the real-time TRMM-based multi-satellite precipitation analysis for an operational flood prediction system in Nzoia Basin, Lake Victoria, Africa. *Nat. Hazards* **2009**, *50*, 109–123. Correction in *Nat. Hazards* **2017**, *89*, 1495. [CrossRef]
76. Wu, J.; Ma, G. 3D simulation of image-defined complex internal features using the numerical manifold method. *Sci. China Technol. Sci.* **2024**, *67*, 1023–1039. [CrossRef]
77. Ranger, N.; Hallegatte, S.; Bhattacharya, S.; Bachu, M.; Priya, S.; Dhore, K.; Rafique, F.; Mathur, P.; Naville, N.; Henriet, F.; et al. An assessment of the potential impact of climate change on flood risk in Mumbai. *Clim. Change* **2011**, *104*, 139–167. [CrossRef]
78. Rouillard, J.J.; Heal, K.V.; Reeves, A.D.; Ball, T. Impact of institutions on flood policy learning. *Water Policy* **2012**, *14*, 232–249. [CrossRef]
79. Li, M.; Yuan, C.; Li, K.; Gao, M.; Zhang, Y.; Lv, H. Knowledge Management Model for Urban Flood Emergency Response Based on Multimodal Knowledge Graphs. *Water* **2024**, *16*, 1676. [CrossRef]
80. Wojciechowska, K.A.; Kok, M. First insight into the probabilistic evacuation criteria in the N etherlands. *J. Flood Risk Manag.* **2013**, *6*, 99–111. [CrossRef]
81. Aahlaad, M.; Mozumder, C.; Tripathi, N.; Pal, I. An object-based image analysis of worldview-3 image for urban flood vulnerability assessment and dissemination through ESRI story maps. *J. Indian Soc. Remote Sens.* **2021**, *49*, 2639–2654. [CrossRef]
82. Fouladi Semnan, A.; Ostad Mirza Tehrani, M.J. Fully Automated Risk and Hazard Assessment for Decision-support (FARHAD): A Cloud-Native Machine-Learning Framework for Worst-Case Scenario Flood-Risk Mapping via Weakline Analysis. *Water Resour. Manag.* **2026**, *40*, 426. [CrossRef]
83. Gupta, H.S.; Mahmud, M.S.; Gupta, A. From calibrated risk to actionable response: A prescriptive analytics pipeline for urban flash floods. *Resilient Cities Struct.* **2026**, *5*, 111–125. [CrossRef]

84. Jiang, R.; Wang, L.; Lin, Y.; Xie, J.; Zhao, Y.; Zhai, J.; Wang, S.; Lu, X. An intelligent decision support framework for generating flood control emergency plan using knowledge graph and fuzzy enhanced entity recognition model. *Environ. Model. Softw.* **2026**, *200*, 106939. [CrossRef]
85. Li, F.; Gu, P.; Yin, J.; Zhang, L.; Fang, X. Interdepartmental Cooperation Mechanisms in Urban Flood Emergency Management: An Information-Consistency Perspective. *Sustainability* **2026**, *18*, 3536. [CrossRef]
86. Liu, X.; Zhao, Y.; Ji, Y.; Xue, T.; Li, Y. Enforced Emergency Collaboration Strategy for Improving Robustness of Emergency Response Networks During Urban Floods. *J. Conting. Cris. Manag.* **2026**, *34*, e70114. [CrossRef]
87. Tran, V.N.; Huan, X.; Das Antar, A.; Banovic, N.; Bednar, J.H.; Bergt, S.M.; Cheng, C.; Dominguez, F.; Fatichi, S.; Gonzalez, R.; et al. Reimagining how flood warnings can inform decision-making and community actions. *Earth's Future* **2026**, *14*, e2026EF008857. [CrossRef]
88. Han, Y.; Liu, J.; Luo, A.; Wang, Y.; Bao, S. Fine-Tuning LLM-Assisted Chinese Disaster Geospatial Intelligence Extraction and Case Studies. *ISPRS Int. J. Geo-Inf.* **2025**, *14*, 79. [CrossRef]
89. Shen, Y.; Guo, Q.; Liu, Z.; Shen, Y.; Jia, Y.; Wei, Y. Prediction of drought-flood prone zones in inland mountainous regions under climate change with assessment and enhancement strategies for disaster resilience in high-standard farmland. *Agric. Water Manag.* **2025**, *309*, 109349. [CrossRef]
90. Pawar, U. An identification and mapping of flood susceptible areas in the Wardha Basin using frequency ratio and statistical index models, India. *Environ. Sci. Pollut. Res.* **2024**, *32*, 1565–1580. [CrossRef] [PubMed]
91. Yan, Z.; Guo, X.; Zhao, Z.; Tang, L. Achieving fine-grained urban flood perception and spatio-temporal evolution analysis based on social media. *Sustain. Cities Soc.* **2024**, *101*, 105077. [CrossRef]
92. Thakur, D.A.; Mohanty, M.P. Exploring the fidelity of satellite precipitation products in capturing flood risks: A novel framework incorporating hazard and vulnerability dimensions over a sensitive coastal multi-hazard catchment. *Sci. Total Environ.* **2024**, *920*, 170884. [CrossRef] [PubMed]
93. Wang, L.; Bian, L.; Leon, A.S.; Yin, Z.; Hu, B. Integrating Policy Instruments for Enhanced Urban Resilience: A Machine Learning and IoT-Based Approach to Flood Mitigation. *Water* **2024**, *16*, 3364. [CrossRef]
94. Hofmeister, M.; Brownbridge, G.; Hillman, M.; Mosbach, S.; Akroyd, J.; Lee, K.F.; Kraft, M. Cross-domain flood risk assessment for smart cities using dynamic knowledge graphs. *Sustain. Cities Soc.* **2024**, *101*, 105113. [CrossRef]
95. Zhu, H.; Meng, J.; Yao, J.; Xu, N. Feasibility of Emergency Flood Traffic Road Damage Assessment by Integrating Remote Sensing Images and Social Media Information. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 369. [CrossRef]
96. Arya, S.; Kumar, A. Green Infrastructure for Sustainable Stormwater Management in an Urban Setting Using SWMM-Based Multicriteria Decision-Making Approach. *J. Hydrol. Eng.* **2024**, *29*, 4023044. [CrossRef]
97. Melendez, A.; Gutierrez Soto, M. Flood Resilience Quantification Framework of Rural Communities: Case Study of Harlan County, Kentucky. *Nat. Hazards Rev.* **2024**, *25*, 5024009. [CrossRef]
98. Zhou, L.; Liu, L. Enhancing dynamic flood risk assessment and zoning using a coupled hydrological-hydrodynamic model and spatiotemporal information weighting method. *J. Environ. Manag.* **2024**, *366*, 121831. [CrossRef] [PubMed]
99. Patel, A.; Yadav, S.M.; Teegavarapu, R. Enhancing real-time flood forecasting and warning system by integrating ensemble techniques and hydrologic model simulations. *J. Water Clim. Change* **2024**, *15*, 4307–4327. [CrossRef]
100. Halder, K.; Ghosh, A.; Srivastava, A.K.; Pal, S.C.; Chatterjee, U.; Bisai, D.; Ewert, F.; Gaiser, T.; Islam, A.R.M.T.; Alam, E.; et al. SAR-driven flood inventory and multi-factor ensemble susceptibility modelling using machine learning frameworks. *Geomat. Nat. Hazards Risk* **2024**, *15*, 2409202. [CrossRef]
101. Nash, S.; Escauriaza, C.; Finaud-Guyot, P.; Jahn, W.; Rousseau, A. Single porosity model: Exploring the spatial resolution limits in complex urban patterns. *J. Hydrol.* **2024**, *637*, 131239. [CrossRef]
102. Srivanit, M.; Pattanasri, S.; Phichetkunbodee, N.; Manokeaw, S.; Sitthikankun, S.; Rinchumphu, D. Analysis of sensitive urban form indicators of flood susceptible prediction based on machine learning models. *Glob. J. Environ. Sci. Manag.* **2024**, *10*, 1501–1518.
103. Twerefou, D.K.; Abeney, J.O.; Larbi, R.T.; Dovie, D.B.K. To live with floods or not: Intersectionality of drivers of urban households' adaptation and relocation intentions. *J. Flood Risk Manag.* **2024**, *17*, e13015. [CrossRef]
104. Al Kuisi, M.; Al Azzam, N.; Hyarat, T.; Farhan, I. Flood Hazard and Risk Assessment of Flash Floods for Petra Catchment Area Using Hydrological and Analytical Hierarchy (AHP) Modeling. *Water* **2024**, *16*, 2283. [CrossRef]
105. Zheng, C.; Yang, W.; Jiang, X.; Lian, J.; Hu, D.; Yan, X.; Yan, L. A novel integrated Urban flood risk assessment approach coupling GeoDetector-Dematel and clustering method. *J. Environ. Manag.* **2024**, *354*, 120308. [CrossRef] [PubMed]
106. Guo, Y.; He, P.; Chen, P.; Zhang, L. Ecological Evaluation of Land Resources in the Yangtze River Delta Region by Remote Sensing Observation. *Land* **2024**, *13*, 1155. [CrossRef]
107. Rufat, S.; Howe, P.D. Small-area estimations from survey data for high-resolution maps of urban flood risk perception and evacuation behavior. *Ann. Am. Assoc. Geogr.* **2023**, *113*, 425–447. [CrossRef]
108. Jiang, S.-H.; Zhi, H.-L.; Wang, Z.Z.; Zhang, S. Enhancing flood risk assessment and mitigation through numerical modeling: A case study. *Nat. Hazards Rev.* **2023**, *24*, 4022046. [CrossRef]

109. Chambers, M.L.; van Rees, C.B.; Bledsoe, B.P.; Crane, D.; Ferreira, S.; Hall, D.M.; Lammers, R.W.; Landry, C.E.; Nelson, D.R.; Shudtz, M.; et al. Nature-based solutions for leveed river corridors. *Anthropocene* **2023**, *44*, 100417. [CrossRef]
110. Khan, A.; Gong, Z.; Shah, A.A.; Haq, M. A multi-criteria decision-making approach to vulnerability assessment of rural flooding in Khyber Pakhtunkhwa Province, Pakistan. *Environ. Sci. Pollut. Res.* **2023**, *30*, 56786–56801. [CrossRef] [PubMed]
111. Tian, J.; Zeng, S.; Zeng, J.; Jiang, F. Assessment of supply and demand of regional flood regulation ecosystem services and zoning management in response to flood disasters: A case study of Fujian delta. *Int. J. Environ. Res. Public Health* **2022**, *20*, 589. [CrossRef] [PubMed]
112. Eghdami, S.; Scheld, A.M.; Louis, G. Socioeconomic vulnerability and climate risk in coastal Virginia. *Clim. Risk Manag.* **2023**, *39*, 100475. [CrossRef]
113. Josipovic, N.; Viergutz, K. Smart solutions for municipal flood management: Overview of literature, trends, and applications in German cities. *Smart Cities* **2023**, *6*, 944–964. [CrossRef]
114. Li, B.; Hou, J.; Wang, X.; Ma, Y.; Li, D.; Wang, T.; Chen, G. High-resolution flood numerical model and dijkstra algorithm based risk avoidance routes planning. *Water Resour. Manag.* **2023**, *37*, 3243–3258. [CrossRef]
115. Jitt-Aer, K.; Wall, G.; Jones, D.; Teeuw, R. Use of GIS and dasymetric mapping for estimating tsunami-affected population to facilitate humanitarian relief logistics: A case study from Phuket, Thailand. *Nat. Hazards* **2022**, *113*, 185–211. [CrossRef]
116. Akbarian, H.; Gheibi, M.; Hajiaghaei-Keshteli, M.; Rahmani, M. A hybrid novel framework for flood disaster risk control in developing countries based on smart prediction systems and prioritized scenarios. *J. Environ. Manag.* **2022**, *312*, 114939. [CrossRef] [PubMed]
117. Abdel-Mooty, M.N.; El-Dakhakhni, W.; Coulibaly, P. Data-driven community flood resilience prediction. *Water* **2022**, *14*, 2120. [CrossRef]
118. Huang, E.-C.; Li, P.-W.; Wu, S.-W.; Lin, C.-Y. Application of Risk Analysis in the Screening of Flood Disaster Hot Spots and Adaptation Strategies. *Land* **2021**, *11*, 36. [CrossRef]
119. Lienert, J.; Andersson, J.C.M.; Hofmann, D.; Pinto, F.S.; Kuller, M. The role of multi-criteria decision analysis in a transdisciplinary process: Co-developing a flood forecasting system in western Africa. *Hydrol. Earth Syst. Sci.* **2022**, *26*, 2899–2922. [CrossRef]
120. An, T.T.; Izuru, S.; Narumasa, T.; Raghavan, V.; Hanh, L.N.; Van An, N.; Long, N.V.; Thuy, N.T.; Minh, T.P. Flood vulnerability assessment at the local scale using remote sensing and GIS techniques: A case study in Da Nang City, Vietnam. *J. Water Clim. Change* **2022**, *13*, 3217. [CrossRef]
121. Chan, A.Y.; Burrows, K.; Bell, M.L. Why They Stayed and Why They Left—A Case Study from Ellicott City, MD after Flash Flooding. *Int. J. Environ. Res. Public Health* **2022**, *19*, 10636. [CrossRef] [PubMed]
122. Bucherie, A.; Hultquist, C.; Adamo, S.; Neely, C.; Ayala, F.; Bazo, J.; Kruczkiewicz, A. A comparison of social vulnerability indices specific to flooding in Ecuador: Principal component analysis (PCA) and expert knowledge. *Int. J. Disaster Risk Reduct.* **2022**, *73*, 102897. [CrossRef]
123. Wei, G.; Liang, G.; Ding, W.; He, B.; Wu, J.; Ren, M.; Zhou, H. Deriving optimal operating rules for flood control considering pre-release based on forecast information. *J. Hydrol.* **2022**, *615*, 128665. [CrossRef]
124. Albright, E.A.; Crow, D.A. Capacity building toward resilience: How communities recover, learn, and change in the aftermath of extreme events. *Policy Stud. J.* **2021**, *49*, 89–122. [CrossRef]
125. Abdi-Dehkordi, M.; Bozorg-Haddad, O.; Salavitabar, A.; Mohammad-Azari, S.; Goharian, E. Development of flood mitigation strategies toward sustainable development. *Nat. Hazards* **2021**, *108*, 2543–2567. [CrossRef]
126. Buarque, A.C.S.; Souza, C.F.; Souza, F.A.A.; Mendiondo, E.M. Urban flood risk under global changes: A socio-hydrological and cellular automata approach in a Brazilian catchment. *Hydrol. Sci. J.* **2021**, *66*, 2011–2021. [CrossRef]
127. Ekmekcioğlu, Ö.; Koc, K.; Özger, M. Stakeholder perceptions in flood risk assessment: A hybrid fuzzy AHP-TOPSIS approach for Istanbul, Turkey. *Int. J. Disaster Risk Reduct.* **2021**, *60*, 102327. [CrossRef]
128. Blázquez, L.; García, J.A.; Bodoque, J.M. Stakeholder analysis: Mapping the river networks for integrated flood risk management. *Environ. Sci. Policy* **2021**, *124*, 506–516. [CrossRef]
129. Axelsson, C.; Giove, S.; Soriani, S. Urban pluvial flood management Part 1: Implementing an AHP-TOPSIS multi-criteria decision analysis method for Stakeholder integration in urban climate and stormwater adaptation. *Water* **2021**, *13*, 2422. [CrossRef]
130. Pham, B.T.; Luu, C.; Van Phong, T.; Nguyen, H.D.; Van Le, H.; Tran, T.Q.; Ta, H.T.; Prakash, I. Flood risk assessment using hybrid artificial intelligence models integrated with multi-criteria decision analysis in Quang Nam Province, Vietnam. *J. Hydrol.* **2021**, *592*, 125815. [CrossRef]
131. Zzaman, R.U.; Nowreen, S.; Billah, M.; Islam, A.S. Flood hazard mapping of Sangu River basin in Bangladesh using multi-criteria analysis of hydro-geomorphological factors. *J. Flood Risk Manag.* **2021**, *14*, e12715. [CrossRef]
132. Keyvanfar, A.; Shafaghat, A.; Ya'acob, N.; Roslan, A. Sustainable post-disaster settlement (SPS) assessment model for evaluating performance of construction management in post-flood risk-reduction and recoVERY. *J. Sustain. Sci. Manag.* **2021**, *16*, 174–199. [CrossRef]

133. Zarekarizi, M.; Roop-Eckart, K.J.; Sharma, S.; Keller, K. The FLOod Probability Interpolation tool (FLOPIT): A simple tool to improve spatial flood probability quantification and communication. *Water* **2021**, *13*, 666. [CrossRef]
134. Tanim, A.H.; Goharian, E. Developing a hybrid modeling and multivariate analysis framework for storm surge and runoff interactions in urban coastal flooding. *J. Hydrol.* **2021**, *595*, 125670. [CrossRef]
135. Petridou, E.; Becker, P.; Sparf, J. Policy entrepreneurs in public administration: A social network analysis. *Polit. Policy* **2021**, *49*, 414–445. [CrossRef]
136. Raikes, J.; Smith, T.F.; Baldwin, C.; Henstra, D. Linking disaster risk reduction and human development. *Clim. Risk Manag.* **2021**, *32*, 100291. [CrossRef]
137. Mubeen, A.; Ruangpan, L.; Vojinovic, Z.; Torrez, A.S.; Plavšić, J. Planning and suitability assessment of large-scale nature-based solutions for flood-risk reduction. *Water Resour. Manag.* **2021**, *35*, 3063–3081. [CrossRef]
138. Lv, H.; Guan, X.; Meng, Y. Study on economic value of urban land resources based on emergy and econometric theories. *Environ. Dev. Sustain.* **2021**, *23*, 1019–1042. [CrossRef]
139. Rajkumar, G.; Narayan, G.; Mohammed Irshad, S. Transboundary disaster governance between India and Nepal-A perspective study on Kosi basin about risk governance dealing policies and communities. *Disaster Adv.* **2020**, *13*, 32–39.
140. Goodrich, K.A.; Basolo, V.; Feldman, D.L.; Matthew, R.A.; Schubert, J.E.; Luke, A.; Eguiarte, A.; Boudreau, D.; Serrano, K.; Reyes, A.S.; et al. Addressing pluvial flash flooding through community-based collaborative research in Tijuana, Mexico. *Water* **2020**, *12*, 1257. [CrossRef]
141. Michaelis, T.; Brandimarte, L.; Mazzoleni, M. Capturing flood-risk dynamics with a coupled agent-based and hydraulic modelling framework. *Hydrol. Sci. J.* **2020**, *65*, 1458–1473. [CrossRef]
142. Salazar-Briones, C.; Ruiz-Gibert, J.M.; Lomelí-Banda, M.A.; Mungaray-Moctezuma, A. An integrated urban flood vulnerability index for sustainable planning in arid zones of developing countries. *Water* **2020**, *12*, 608. [CrossRef]
143. Xu, W.; Xiang, L.; Proverbs, D. Assessing community resilience to urban flooding in multiple types of the transient population in China. *Water* **2020**, *12*, 2784. [CrossRef]
144. Koc, K.; Işık, Z. A multi-agent-based model for sustainable governance of urban flood risk mitigation measures. *Nat. Hazards* **2020**, *104*, 1079–1110. [CrossRef]
145. Casado, M.R.; Leinster, P. Towards more effective strategies to reduce property level flood risk: Standardising the use of Unmanned Aerial Vehicles. *J. Water Supply Res. Technol.* **2020**, *69*, 807–818. [CrossRef]
146. Howarth, C.; Morse-Jones, S.; Kythreotis, A.; Brooks, K.; Lane, M. Informing UK governance of resilience to climate risks: Improving the local evidence-base. *Clim. Change* **2020**, *163*, 499–520. [CrossRef]
147. Thaler, T.; Seebauer, S.; Schindelegger, A. Patience, persistence and pre-signals: Policy dynamics of planned relocation in Austria. *Glob. Environ. Change* **2020**, *63*, 102122. [CrossRef]
148. Sanders, B.F.; Schubert, J.E.; Goodrich, K.A.; Houston, D.; Feldman, D.L.; Basolo, V.; Luke, A.; Boudreau, D.; Karlin, B.; Cheung, W.; et al. Collaborative modeling with fine-resolution data enhances flood awareness, minimizes differences in flood perception, and produces actionable flood maps. *Earth's Future* **2020**, *8*, e2019EF001391. [CrossRef]
149. Koutiva, I.; Lykou, A.; Pantazis, C.; Makropoulos, C. Investigating decision mechanisms of statutory stakeholders in flood risk strategy formation: A computational experiments approach. *Water* **2020**, *12*, 2716. [CrossRef]
150. Chen, J.; Li, Q.; Wang, H.; Deng, M. A machine learning ensemble approach based on random forest and radial basis function neural network for risk evaluation of regional flood disaster: A case study of the Yangtze River Delta, China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 49. [CrossRef] [PubMed]
151. Towe, R.; Dean, G.; Edwards, L.; Nundloll, V.; Blair, G.; Lamb, R.; Hankin, B.; Manson, S. Rethinking data-driven decision support in flood risk management for a big data age. *J. Flood Risk Manag.* **2020**, *13*, e12652. [CrossRef]
152. Zou, Q.; Liao, L.; Qin, H. Fast comprehensive flood risk assessment based on game theory and cloud model under parallel computation (P-GT-CM). *Water Resour. Manag.* **2020**, *34*, 1625–1648. [CrossRef]
153. Maskrey, S.; Vilcan, T.; O'Donnell, E.; Lamond, J. Using Learning and Action Alliances to build capacity for local flood risk management. *Environ. Sci. Policy* **2020**, *107*, 198–205. [CrossRef]
154. Bisaro, A.; de Bel, M.; Hinkel, J.; Kok, S.; Stojanovic, T.; Ware, D. Multilevel governance of coastal flood risk reduction: A public finance perspective. *Environ. Sci. Policy* **2020**, *112*, 203–212. [CrossRef]
155. Jeffers, J. Barriers to transformation towards participatory adaptation decision-making: Lessons from the Cork flood defences dispute. *Land Use Policy* **2020**, *90*, 104333. [CrossRef]
156. Mahmood, S.; Rahman, A.; Shaw, R. Spatial appraisal of flood risk assessment and evaluation using integrated hydro-probabilistic approach in Panjkora River Basin, Pakistan. *Environ. Monit. Assess.* **2019**, *191*, 573. [CrossRef] [PubMed]
157. Ghosh, T.K.; Jakobsen, F.; Joshi, M.; Pareta, K. Extreme rainfall and vulnerability assessment: Case study of Uttarakhand rivers. *Nat. Hazards* **2019**, *99*, 665–687. [CrossRef]

158. Ardaya, A.B.; Evers, M.; Ribbe, L. Participatory approaches for disaster risk governance? Exploring participatory mechanisms and mapping to close the communication gap between population living in flood risk areas and authorities in Nova Friburgo Municipality, RJ, Brazil. *Land Use Policy* **2019**, *88*, 104103. [CrossRef]
159. Van Hoang, T.; Chou, T.Y.; Nguyen, N.T.; Fang, Y.M.; Yeh, M.L.; Nguyen, Q.H.; Nguyen, X.L. A robust early warning system for preventing flash floods in mountainous area in Vietnam. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 228. [CrossRef]
160. Brockhoff, R.C.; Koop, S.H.A.; Snel, K.A.W. Pluvial flooding in utrecht: On its way to a flood-proof city. *Water* **2019**, *11*, 1501. [CrossRef]
161. Chen, N.; Yao, S.; Wang, C.; Du, W. A method for urban flood risk assessment and zoning considering road environments and terrain. *Sustainability* **2019**, *11*, 2734. [CrossRef]
162. Weber, K.; Wernhart, S.; Stickler, T.; Fuchs, B.; Balas, M.; Hübl, J.; Damyanovic, D. Risk communication on floodings: Insights into the risk awareness of migrants in rural communities in Austria. *Mt. Res. Dev.* **2019**, *39*, D14–D26. [CrossRef]
163. Leskens, J.G.; Brugnach, M.; Hoekstra, A. How do interactive flood simulation models influence decision-making? An observations-based evaluation method. *Water* **2019**, *11*, 2427. [CrossRef]
164. Pagano, A.; Pluchinotta, I.; Pengal, P.; Cokan, B.; Giordano, R. Engaging stakeholders in the assessment of NBS effectiveness in flood risk reduction: A participatory System Dynamics Model for benefits and co-benefits evaluation. *Sci. Total Environ.* **2019**, *690*, 543–555. [CrossRef] [PubMed]
165. Barker, J.L.P.; Macleod, C.J.A. Development of a national-scale real-time Twitter data mining pipeline for social geodata on the potential impacts of flooding on communities. *Environ. Model. Softw.* **2019**, *115*, 213–227. [CrossRef]
166. Komolafe, A.A.; Herath, S.; Avtar, R.; Vuillaume, J.-F. Comparative analyses of flood damage models in three Asian countries: Towards a regional flood risk modelling. *Environ. Syst. Decis.* **2019**, *39*, 229–246. [CrossRef]
167. Ramsey, M.M.; Muñoz-Erickson, T.A.; Mélendez-Ackerman, E.; Nytch, C.J.; Branoff, B.L.; Carrasquillo-Medrano, D. Overcoming barriers to knowledge integration for urban resilience: A knowledge systems analysis of two-flood prone communities in San Juan, Puerto Rico. *Environ. Sci. Policy* **2019**, *99*, 48–57. [CrossRef]
168. Wu, Y.; Peng, F.; Peng, Y.; Kong, X.; Liang, H.; Li, Q. Dynamic 3D simulation of flood risk based on the integration of spatio-temporal GIS and hydrodynamic models. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 520. [CrossRef]
169. Houessou-Dossou, E.A.Y.; Gathenya, J.M.; Njuguna, M.; Gariy, Z.A. Flood frequency analysis using participatory GIS and rainfall data for two stations in Narok Town, Kenya. *Hydrology* **2019**, *6*, 90. [CrossRef]
170. Shao, W.; Xian, S.; Lin, N.; Kunreuther, H.; Jackson, N.; Goidel, K. Understanding the effects of past flood events and perceived and estimated flood risks on individuals' voluntary flood insurance purchase behavior. *Water Res.* **2017**, *108*, 391–400. [CrossRef] [PubMed]
171. Pasquier, U.; He, Y.; Hooton, S.; Goulden, M.; Hiscock, K.M. An integrated 1D–2D hydraulic modelling approach to assess the sensitivity of a coastal region to compound flooding hazard under climate change. *Nat. Hazards* **2019**, *98*, 915–937. [CrossRef]
172. Wang, S.; Zhang, W.; Chen, F. Simulation of drainage capacity in a coastal nuclear power plant under extreme rainfall and tropical storm. *Sustainability* **2019**, *11*, 642. [CrossRef]
173. Sun, J.; Ding, L.; Li, J.; Qian, H.; Huang, M.; Xu, N. Monitoring temporal change of river islands in the Yangtze River by remotely sensed data. *Water* **2018**, *10*, 1484. [CrossRef]
174. Schwanenberg, D.; Natschke, M.; Todini, E.; Reggiani, P. Scientific, technical and institutional challenges towards next-generation operational flood risk management decision support systems. *Int. J. River Basin Manag.* **2018**, *16*, 345–352. [CrossRef]
175. Olsen, V.B.K.; Momen, B.; Langsdale, S.M.; Galloway, G.E.; Link, E.; Brubaker, K.L.; Ruth, M.; Hill, R.L. An approach for improving flood risk communication using realistic interactive visualisation. *J. Flood Risk Manag.* **2018**, *11*, S783–S793. [CrossRef]
176. Williams, D.S.; Costa, M.M.; Celliers, L.; Sutherland, C. Informal settlements and flooding: Identifying strengths and weaknesses in local governance for water management. *Water* **2018**, *10*, 871. [CrossRef]
177. Cabal, A.; Erlich, M. Flood risk management approaches and tools for mitigation strategies of coastal submersions and preparedness of crisis management in France. *Int. J. River Basin Manag.* **2018**, *16*, 353–369. [CrossRef]
178. Isahak, A.; Reza, M.I.; Siwar, C.; Ismail, S.M.; Sulaiman, N.; Hanafi, Z.; Zainuddin, M.S.; Taha, M.R. Delineating risk zones and evaluation of shelter centres for flood disaster management along the Pahang River Basin, Malaysia. *Jàmbá J. Disaster Risk Stud.* **2018**, *10*, 501. [CrossRef] [PubMed]
179. Luu, C.; Von Meding, J. A flood risk assessment of Quang Nam, Vietnam using spatial multicriteria decision analysis. *Water* **2018**, *10*, 461. [CrossRef]
180. Yang, C.-L.; Shieh, M.-C.; Huang, C.-Y.; Tung, C.-P. A derivation of factors influencing the successful integration of corporate volunteers into public flood disaster inquiry and notification systems. *Sustainability* **2018**, *10*, 1973. [CrossRef]
181. Hatzikyriakou, A.; Lin, N. Assessing the vulnerability of structures and residential communities to storm surge: An analysis of flood impact during Hurricane Sandy. *Front. Built Environ.* **2018**, *4*, 4. [CrossRef]
182. Wan, K.M.; Billa, L. Post-flood land use damage estimation using improved Normalized Difference Flood Index (NDFI3) on Landsat 8 datasets: December 2014 floods, Kelantan, Malaysia. *Arab. J. Geosci.* **2018**, *11*, 434. [CrossRef]

183. Luu, C.; Von Meding, J.; Kanjanabootra, S. Flood risk management activities in Vietnam: A study of local practice in Quang Nam province. *Int. J. Disaster Risk Reduct.* **2018**, *28*, 776–787. [CrossRef]
184. Zevenbergen, C.; Khan, S.A.; van Alphen, J.; van Scheltinga, C.T.; Veerbeek, W. Adaptive delta management: A comparison between the Netherlands and Bangladesh Delta Program. *Int. J. River Basin Manag.* **2018**, *16*, 299–305. [CrossRef]
185. Straatsma, M.W.; Kleinhans, M.G. Flood hazard reduction from automatically applied landscaping measures in RiverScape, a Python package coupled to a two-dimensional flow model. *Environ. Model. Softw.* **2018**, *101*, 102–116. [CrossRef]
186. Tang, M.; Liao, H.; Li, Z.; Xu, Z. Nature disaster risk evaluation with a group decision making method based on incomplete hesitant fuzzy linguistic preference relations. *Int. J. Environ. Res. Public Health* **2018**, *15*, 751. [CrossRef] [PubMed]
187. He, Y.; Wan, J.; Lei, X.; Singh, H. Flood disaster level evaluation using a particle swarm optimization algorithm considering decision maker's preference. *Water Sci. Technol. Water Supply* **2018**, *18*, 288–298. [CrossRef]
188. Begg, C.; Callsen, I.; Kuhlicke, C.; Kelman, I. The role of local stakeholder participation in flood defence decisions in the United Kingdom and Germany. *J. Flood Risk Manag.* **2018**, *11*, 180–190. [CrossRef]
189. Seenirajan, M.; Natarajan, M.; Thangaraj, R.; Kavitha, E. Flood disaster preventive measures using GIS and multicriteria technique in the water sheds area of Ambasamuthiram Town. *Ecol. Environ. Conserv* **2018**, *24*, 1937–1945.
190. Ryu, J.; Yoon, E.J.; Park, C.; Lee, D.K.; Jeon, S.W. A flood risk assessment model for companies and criteria for governmental decision-making to minimize hazards. *Sustainability* **2017**, *9*, 2005. [CrossRef]
191. Wu, Y.; Zhong, P.; Xu, B.; Zhu, F.; Ma, B. Changing of flood risk due to climate and development in Huaihe River basin, China. *Stoch. Environ. Res. Risk Assess.* **2017**, *31*, 935–948. [CrossRef]
192. Lopez, M.G.; Di Baldassarre, G.; Seibert, J. Impact of social preparedness on flood early warning systems. *Water Resour. Res.* **2017**, *53*, 522–534. [CrossRef]
193. Raikes, J.; McBean, G. Institutional response to disaster risk: The City of Vancouver and District of Maple Ridge, British Columbia, Canada. *Reg. Environ. Change* **2017**, *17*, 2433–2441. [CrossRef]
194. Sherry, J.; Curtis, A. At the intersection of disaster risk and religion: Interpretations and responses to the threat of Tsho Rolpa glacial lake. *Environ. Hazards* **2017**, *16*, 314–329. [CrossRef]
195. Bajic, S.; Popov, S. Flood hazard analysis-GIS aspects of possible solution. *Fresenius Environ. Bull.* **2017**, *26*, 5041–5048.
196. Wiering, M.; Winnubst, M. The conception of public interest in Dutch flood risk management: Untouchable or transforming? *Environ. Sci. Policy* **2017**, *73*, 12–19. [CrossRef]
197. Karamouz, M.; Zahmatkesh, Z. Quantifying resilience and uncertainty in coastal flooding events: Framework for assessing urban vulnerability. *J. Water Resour. Plan. Manag.* **2017**, *143*, 4016071. [CrossRef]
198. Leskens, J.G.; Kehl, C.; Tutenel, T.; Kol, T.; de Haan, G.; Stelling, G.; Eisemann, E. An interactive simulation and visualization tool for flood analysis usable for practitioners. *Mitig. Adapt. Strateg. Glob. Change* **2017**, *22*, 307–324. [CrossRef] [PubMed]
199. Howarth, W. Integrated water resources management and reform of flood risk management in England. *J. Environ. Law* **2017**, *29*, 355–365. [CrossRef]
200. Su, Y.; Sun, X.; Zhao, F. Trust and its effects on the public's perception of flood risk: A social science investigation of the middle and lower reaches of the Yangtze River. *J. Flood Risk Manag.* **2017**, *10*, 487–498. [CrossRef]
201. Boulomytis, V.T.G.; Zuffo, A.C.; Imteaz, M.A. Hydrological impacts of urban developments: Modelling and decision-making concepts. *Theor. Empir. Res. Urban Manag.* **2017**, *12*, 5–19.
202. Liu, J.; Shi, Z. Quantifying land-use change impacts on the dynamic evolution of flood vulnerability. *Land Use Policy* **2017**, *65*, 198–210. [CrossRef]
203. Alamdar, F.; Kalantari, M.; Rajabifard, A. Understanding the provision of multi-agency sensor information in disaster management: A case study on the Australian state of Victoria. *Int. J. Disaster Risk Reduct.* **2017**, *22*, 475–493. [CrossRef]
204. Surminski, S.; Thieken, A.H. Promoting flood risk reduction: The role of insurance in Germany and England. *Earth's Future* **2017**, *5*, 979–1001. [CrossRef]
205. Qiu, L.; Du, Z.; Zhu, Q.; Fan, Y. An integrated flood management system based on linking environmental models and disaster-related data. *Environ. Model. Softw.* **2017**, *91*, 111–126. [CrossRef]
206. Wing, O.E.J.; Bates, P.D.; Sampson, C.C.; Smith, A.M.; Johnson, K.A.; Erickson, T.A. Validation of a 30 m resolution flood hazard model of the conterminous United States. *Water Resour. Res.* **2017**, *53*, 7968–7986. [CrossRef]
207. Albano, C.M.; Dettinger, M.D.; McCarthy, M.I.; Schaller, K.D.; Welborn, T.L.; Cox, D.A. Application of an extreme winter storm scenario to identify vulnerabilities, mitigation options, and science needs in the Sierra Nevada mountains, USA. *Nat. Hazards* **2016**, *80*, 879–900. [CrossRef]
208. Evers, M.; Jonoski, A.; Almoradie, A.; Lange, L. Collaborative decision making in sustainable flood risk management: A socio-technical approach and tools for participatory governance. *Environ. Sci. Policy* **2016**, *55*, 335–344. [CrossRef]
209. Tate, E.; Strong, A.; Kraus, T.; Xiong, H. Flood recovery and property acquisition in Cedar Rapids, Iowa. *Nat. Hazards* **2016**, *80*, 2055–2079. [CrossRef]

210. Maqsood, T.; Wehner, M.; Dale, K.; Edwards, M. Cost-effective mitigation strategies for residential buildings in Australian flood plains. *Flood Risk Manag. Response* **2016**, *6*, 550–559. [CrossRef]
211. Mirfenderesk, H.; Carroll, D.; Chong, E.; Jafari, A. New generation flood forecasting and decision support system for emergency management. *Aust. J. Emerg. Manag.* **2016**, *31*, 31–37.
212. Frank, E.; Ramsbottom, D.; Avanzi, A. Flood risk assessment and prioritisation of measures: Two key tools in the development of a national programme of flood risk management measures in Moldova. *Flood Risk Manag. Response* **2016**, *6*, 475–484. [CrossRef]
213. Thaler, T.A.; Priest, S.J.; Fuchs, S. Evolving inter-regional co-operation in flood risk management: Distances and types of partnership approaches in Austria. *Reg. Environ. Change* **2016**, *16*, 841–853. [CrossRef]
214. Youssef, A.M.; Pradhan, B.; Sefry, S.A. Flash flood susceptibility assessment in Jeddah city (Kingdom of Saudi Arabia) using bivariate and multivariate statistical models. *Environ. Earth Sci.* **2016**, *75*, 12. [CrossRef]
215. Thaler, T.; Levin-Keitel, M. Multi-level stakeholder engagement in flood risk management—A question of roles and power: Lessons from England. *Environ. Sci. Policy* **2016**, *55*, 292–301. [CrossRef]
216. Mojtahedi, S.M.H.; Oo, B.L. Coastal buildings and infrastructure flood risk analysis using multi-attribute decision-making. *J. Flood Risk Manag.* **2016**, *9*, 87–96. [CrossRef]
217. Nafari, R.H.; Ngo, T.; Lehman, W. Development and evaluation of FLFAcs–A new Flood Loss Function for Australian commercial structures. *Int. J. Disaster Risk Reduct.* **2016**, *17*, 13–23. [CrossRef]
218. Berariu, R.; Fikar, C.; Gronalt, M.; Hirsch, P. Resource deployment under consideration of conflicting needs in times of river floods. *Disaster Prev. Manag. An. Int. J.* **2016**, *25*, 649–663. [CrossRef]
219. Mees, H.; Crabbé, A.; Alexander, M.; Kaufmann, M.; Bruzzone, S.; Lévy, L.; Lewandowski, J. Coproducing flood risk management through citizen involvement: Insights from cross-country comparison in Europe. *Ecol. Soc.* **2016**, *21*, 417. [CrossRef]
220. Kuhlicke, C.; Callsen, I.; Begg, C. Reputational risks and participation in flood risk management and the public debate about the 2013 flood in Germany. *Environ. Sci. Policy* **2016**, *55*, 318–325. [CrossRef]
221. Hung, K.-C.; Kalantari, M.; Rajabifard, A. Methods for assessing the credibility of volunteered geographic information in flood response: A case study in Brisbane, Australia. *Appl. Geogr.* **2016**, *68*, 37–47. [CrossRef]
222. Challies, E.; Newig, J.; Thaler, T.; Kochskämper, E.; Levin-Keitel, M. Participatory and collaborative governance for sustainable flood risk management: An emerging research agenda. *Environ. Sci. Policy* **2016**, *55*, 275–280. [CrossRef]
223. Dos Santos, P.P.; Tavares, A.O. Basin flood risk management: A territorial data-driven approach to support decision-making. *Water* **2015**, *7*, 480–502. [CrossRef]
224. Brody, S.D.; Highfield, W.E.; Blessing, R. An analysis of the effects of land use and land cover on flood losses along the Gulf of Mexico coast from 1999 to 2009. *JAWRA J. Am. Water Resour. Assoc.* **2015**, *51*, 1556–1567. [CrossRef]
225. Albano, R.; Mancusi, L.; Sole, A.; Adamowski, J. Collaborative strategies for sustainable EU flood risk management: FOSS and geospatial tools—Challenges and opportunities for operative risk analysis. *ISPRS Int. J. Geo-Inf.* **2015**, *4*, 2704–2727. [CrossRef]
226. Barbedo, J.; Miguez, M.; Van der Horst, D.; Carneiro, P.; Amis, P.; Ioris, A. Policy dimensions of land-use change in peri-urban floodplains: The case of Paraty. *Ecol. Soc.* **2015**, *20*, 1–11. [CrossRef]
227. Penning-Rowsell, E.C.; Johnson, C. The ebb and flow of power: British flood risk management and the politics of scale. *Geoforum* **2015**, *62*, 131–142. [CrossRef]
228. Wiering, M.; Green, C.; van Rijswick, M.; Priest, S.; Keessen, A. The rationales of resilience in English and Dutch flood risk policies. *J. Water Clim. Change* **2015**, *6*, 38–54. [CrossRef]
229. Ding, Y.; Zhu, Q.; Lin, H. An integrated virtual geographic environmental simulation framework: A case study of flood disaster simulation. *Geo-Spat. Inf. Sci.* **2014**, *17*, 190–200. [CrossRef]
230. Canters, F.; Vanderhaegen, S.; Khan, A.Z.; Engelen, G.; Uljee, I. Land-use simulation as a supporting tool for flood risk assessment and coastal safety planning: The case of the Belgian coast. *Ocean Coast. Manag.* **2014**, *101*, 102–113. [CrossRef]
231. Cheong, T.S.; Felix, M.L.A.; Jeong, S.M. Development of GIS-based disaster assessment system to reduce flood risks in urbanized creeks. *Desalin. Water Treat.* **2014**, *52*, 2817–2825. [CrossRef]
232. Bevilacqua, M.; Ciarapica, F.E.; Paciarotti, C. A BPR approach to hydrogeological risk management. *Nat. Hazards* **2014**, *71*, 1995–2012. [CrossRef]
233. Kolen, B.; Helsloot, I. Decision-making and evacuation planning for flood risk management in the Netherlands. *Disasters* **2014**, *38*, 610–635. [CrossRef] [PubMed]
234. Othman, M.; Ahmad, M.N.; Suliman, A.; Arshad, N.H.; Maidin, S.S. COBIT principles to govern flood management. *Int. J. Disaster Risk Reduct.* **2014**, *9*, 212–223. [CrossRef]
235. Wang, Y.; Zhou, B.; Xu, Y.; Chung, C.Y.; Yang, Y.; Yuan, Z.; Hu, C. Spatio-temporal power outage risk prediction for interdependent urban electricity and drainage networks under rainstorm disasters. *IEEE Trans. Smart Grid* **2026**, *17*, 2888–2902. [CrossRef]
236. Hua, Z.; Zhou, B.; Chan, K.W.; Zhang, C.; Cao, Y.; Wang, P.; Xia, M. A progressive polyhedral approximation method for nonlinear PDE-constrained electricity-water nexus dispatch. *IEEE Trans. Smart Grid* **2025**, *16*, 2703–2706. [CrossRef]

237. Xia, Y.; Zheng, D.; Zhang, Y.; Deng, W.; Yang, T. Balancing urban environmental and societal performance in high-density cities: Morphological trade-offs and optimization strategies in Shenzhen and Hong Kong. *Sustain. Cities Soc.* **2026**, *143*, 107383. [CrossRef]
238. Zhang, X.; Zheng, H.; Li, J.; Xie, Z.; Sun, H.; Wang, H. Safety decision-making for autonomous vehicles integrating passenger physiological states by fNIRS. *Cyborg Bionic Syst.* **2025**, *6*, 0205. [CrossRef] [PubMed]
239. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef] [PubMed]

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