Review

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A Systematic Literature Review on IoT-Enabled Flood Disaster Mitigation Systems: Technologies, Challenges, and Future Directions

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***Abstract*–Flood disasters are happening more often and are getting worse because of climate change and urbanization. This means that we need advanced mitigation systems that use the latest technologies. This systematic literature review analyzes IoT-enabled flood disaster mitigation systems, emphasizing their technological underpinnings, implementation obstacles, and prospective research trajectories. We examine the functions of IoT and AI in flood management, flood risk assessment methodologies, and mitigation strategies, while also investigating the social and economic consequences of floods and the application of remote sensing, UAVs, and social media in disaster communication. The review employs a systematic approach to identify, assess, and integrate pertinent studies, guaranteeing a thorough comprehension of the present research landscape. Our research shows that IoT-based systems greatly enhance the ability to monitor floods in real time and give early warnings. However, there are still challenges.**

***Keywords:* Internet of Things (IoT), Flood Disaster Mitigation, Artificial Intelligence and Machine Learning, Real-Time Flood Monitoring, Early Warning Systems, Remote Sensing and UAVs, Smart Disaster Management Systems, Climate-Resilient Infrastructure.**

I. INTRODUCTION

Floods are one of the most destructive natural disasters, destroying infrastructure, ecosystems, and human lives on a large scale. Climate change and rapid urbanization have made floods more common and stronger, which has led to the need for better mitigation systems [1]. Old ways of keeping an eye on floods and responding to them often depend on manual observations and static sensor networks, which aren't good enough for making decisions in real time when floods are changing [2]. The Internet of Things (IoT) has changed flood disaster mitigation systems in a big way by making it possible to collect data in real time, analyze it automatically, and coordinate responses quickly [3].

The basis for IoT-enabled flood mitigation systems is the coming together of sensor technologies, wireless communication, and data analytics. IoT devices like weather stations, water level sensors, and flow meters constantly monitor the environment. Cloud computing and edge processing make it possible to interpret data in real time [4].

Artificial intelligence (AI) makes these systems even better by using machine learning models trained on both past and present data to make flood predictions more accurate [5].

Remote sensing technologies, such as satellite imagery and unmanned aerial vehicles (UAVs), enhance ground-based IoT networks by providing extensive flood mapping and damage assessment [6].

Even with these improvements, there are still big gaps in research in this area. Many current IoT-based flood mitigation systems have problems with interoperability, which means that different devices and platforms have trouble sharing data smoothly [7]. Energy efficiency is another important issue because IoT sensors that run on batteries in remote areas that are prone to flooding often have problems with their operations [8]. Also, AI-based flood prediction models look promising, but we don't know how well they work in very bad weather [9]. Data privacy and fair access to early warning systems are two social and ethical issues that need more study [10].

The impetus for this systematic literature review arises from the pressing necessity to consolidate current knowledge regarding IoT-enabled flood mitigation systems and to delineate avenues for future research. This review seeks to offer a thorough comprehension of technological progress, implementation challenges, and nascent trends in the domain by synthesizing findings from various studies. This work is important because it could help policymakers, researchers, and practitioners come up with better flood mitigation plans that are more resilient and inclusive.

A. Research Gap and Contributions

Even though IoT-enabled flood disaster mitigation systems are improving quickly, the current literature shows that there are still some important gaps that make them less effective and harder to use on a large scale.

First, most studies look at only one piece of technology at a time, like IoT-based sensing, AI models, or remote sensing techniques. They don't look at how these technologies can work together as a whole system. This broken-up method makes it harder to create complete and interoperable flood mitigation frameworks.

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Second, IoT platforms and communication protocols are not standardized or interoperable, which makes it hard for different systems and institutions to share data easily. Many current solutions are created in controlled settings and do not solve integration problems that happen in the real world.

Third, even though machine learning and deep learning models have shown promise in predicting floods, we still don't know enough about how reliable they are in extreme and uncertain situations. Most studies use historical datasets, which may not accurately reflect future flood scenarios caused by climate change.

Fourth, people often forget about the energy efficiency and long-term viability of IoT installations in areas that are far away and prone to flooding. Long-term system performance is greatly affected by battery limitations and maintenance issues.

Fifth, the social and institutional aspects of flood mitigation systems are inadequately represented. Concerns like fair access to early warning systems, community involvement, governance structures, and ethical issues around data privacy are not often included in technical studies.

Finally, there are very few comprehensive conceptual frameworks that bring together technological, environmental, and socio-economic factors into one analytical model. This gap makes it harder for researchers and policymakers to come up with flood mitigation plans that work for a lot of people and can be used in a lot of places.

To fill the gaps that were found, this study makes the following important contributions:

- Full Systematic Review
- A framework that includes many dimensions
- A list of technologies and their uses
- A Critical Look at the Problems with Implementation
- Finding new trends and research opportunities
- Connecting Technology and Policy Points of View
- Advice for future research and practice

The remainder of this paper is organized as follows: Section 2 outlines the methodology adopted for this systematic literature review, including the selection criteria and analysis framework. Section 3 presents the results, structured into subsections covering research trends, IoT and AI applications, flood risk assessment, mitigation strategies, social and economic impacts, remote sensing, disaster communication, and management frameworks. Section 4 discusses the findings in the context of current challenges and future opportunities, while Section 5 concludes the review with key takeaways and recommendations.

II. METHODOLOGY

A. *Review Protocol*

This systematic literature review adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines [11] to guarantee methodological rigor and transparency. The research utilizes a multi-database search strategy to identify pertinent publications regarding IoT-enabled flood disaster mitigation systems. IEEE Xplore was given priority because it has a large collection of peer-reviewed technical papers on IoT and disaster management. We chose Scopus and Web of Science because they cover a lot of interdisciplinary research, and ScienceDirect and SpringerLink because they have high-impact journal articles. The ACM Digital Library was included to keep track of changes in computational methods, and arXiv was looked at for new preprints. Google Scholar was a helpful extra source for finding more grey literature.

The search strings put together words about IoT ("IoT" OR "Internet of Things") and words about flood mitigation ("flood disaster mitigation system" OR "flood prevention system" OR "flood response system"). We only looked at articles from 2020 and later to keep the focus on recent developments. We also used the NOT operator to leave out review articles.

B. *Research Dimensions*

The framework for analysis divides the literature into seven main themes. IoT and AI in Flood Management looks at how sensor networks and machine learning can be used together for real-time monitoring and predictive analytics. Flood Risk Assessment and Mapping is all about finding ways to model floods in space and figure out how vulnerable people are to them. Flood Mitigation and Response Strategies looks at both structural and non-structural solutions, such as early warning systems and infrastructure that can change to fit the needs of the situation. Social and Economic Impacts of Floods looks at how communities can bounce back, how to weigh the costs and benefits of disaster recovery, and fairness issues. Remote Sensing and UAVs in Flood Monitoring talks about using satellites and drones to keep an eye on floods over a wide area. Social Media and Disaster Communication looks at how people can help each other during floods by sharing information and getting involved. Finally, Disaster Management Frameworks and Systems looks at governance models and interoperability standards for IoT deployments.

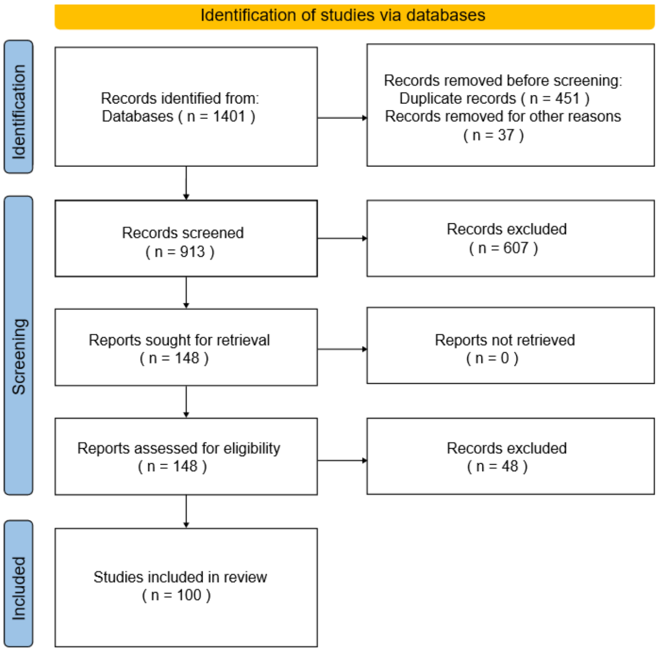

Fig. 1. PRISMA flowchart of study selection

C. *Inclusion and Exclusion Criteria*

Studies were included if they: (1) focused on IoT applications in flood mitigation, (2) were published in English from 2020 to 2024, (3) provided empirical results or theoretical frameworks, and (4) were subject to peer review. The exclusion criteria removed studies that lacked adequate technical detail, were published in languages other than English, or had a tangential focus (for instance, general discussions on climate change that did not connect to IoT).

D. *Study Selection Process*

The initial search yielded 1,401 records, which were deduplicated to 913 unique entries. Title and abstract screening excluded 607 irrelevant studies, followed by full-text assessment of 148 articles. Of these, 48 were excluded for not meeting eligibility criteria, resulting in 100 studies for final synthesis. Figure 1 illustrates the PRISMA workflow.

Potential biases include database-specific coverage gaps and the exclusion of non-peer-reviewed sources, which may omit practical implementations reported in grey literature. Nevertheless, the rigorous screening process ensures the selected studies align with the research dimensions.

III. RESULTS

A. *Research Trends*

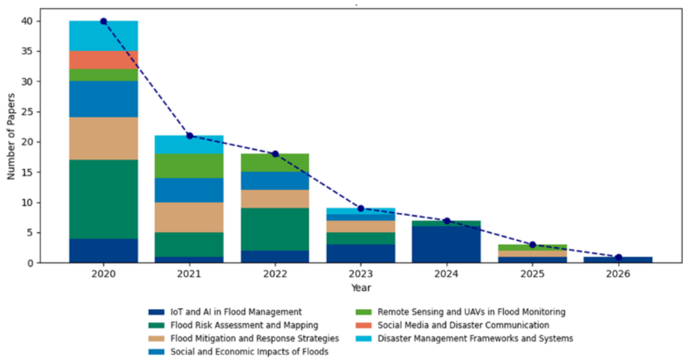

Fig. 2. Research trends in IoT-enabled flood disaster mitigation systems

The examination of publication trends uncovers notable temporal and thematic transitions in IoT-enabled flood disaster mitigation research. The year 2020 stands out in the literature with 40 publications, making up 40% of all the studies reviewed. This shows that interest has grown along with more floods and better technology. In the years that followed, the number of studies slowly dropped, with 21 in 2021, 18 in 2022, and fewer than 10 each year starting in 2023. This trajectory indicates an initial exploratory phase succeeded by consolidation; however, the insufficient data for 2024-2026 precludes conclusive determinations regarding long-term trends.

Thematic distribution shows how research priorities are changing. Flood Risk Assessment and Mapping was the most popular topic in 2020, with 13 publications. This shows that it is based on basic work in spatial analysis and vulnerability modeling. But its popularity waned in later years, making way for IoT and AI in Flood Management. This trend gained speed from 2023 onward, with six publications in 2024. This change is similar to how machine learning is becoming more common in sensor networks for predictive analytics. Flood Mitigation and Response Strategies kept getting attention throughout the time, but the Social and Economic Impacts of Floods started to go down after reaching their highest point in 2020.

The data shows a number of interesting trends. Remote sensing and UAV applications, while initially limited, exhibited consistent growth, reflecting ongoing interest in aerial monitoring technologies. On the other hand, Social Media and Disaster Communication seems to be a small field with only three studies in 2020. This suggests that there is still room for improvement in crowdsourced flood data integration. Disaster Management Frameworks show inconsistent focus, which shows that IoT system governance needs to be done in a more organized way. These trends together show how the field has moved from basic risk modeling to more advanced technological integration, while also pointing out that there are still gaps in the design of socio-technical systems.

B. *IoT and AI Integration in Flood Management Systems*

The integration of IoT and artificial intelligence has transformed flood management from reactive to proactive systems. IoT networks provide real-time environmental monitoring through distributed sensor arrays, while AI algorithms analyze these data streams to predict flood risks and optimize response strategies. This synergy enables dynamic decision-making that traditional static monitoring systems cannot achieve.

Table 1 categorizes the reviewed studies into functional taxonomies based on their technological contributions to flood management:

TABLE I. TAXONOMY OF IOT AND AI APPLICATIONS IN FLOOD MANAGEMENT

Application Area	**Technology Focus**	**Specific Functionality**	**Sources**
Flood Detection & Monitoring	IoT-Based Systems	Urban flood detection	[12]
		Dam surveillance	[13]
		Urban drainage systems	[14]
	AI/ML-Driven Systems	Enhanced monitoring and prevention	[15], [16]
		Flood water body extraction (SAR images)	[17]
		Spatiotemporal forecasting (remote sensing)	[18]
Flood Forecasting & Risk Assessment	Machine Learning Models	Hybrid ML for cloud-based systems	[19]
		Big data and crowdsource integration	[20]
		Flood susceptibility mapping	[21]
	Deep Learning Models	ConvLSTM hybrid algorithm	[22]
		River flooding anomaly detection	[16]
Disaster Response & Management	AI for Disaster Phases	Mitigation, preparedness, response, recovery	[23], [24]
	Smart Emergency Systems	Crisis and disaster resilience	[25]
	Public Risk Communication	GIS-integrated LLM for risk perception	[26]

Application Area	Technology Focus	Specific Functionality	Sources
Adaptive Systems	AI-Enabled IoT	Adaptive flood management	[27]
	Responsible AI Deployment	Water system integration	[28]
Spatial & Data Integration	Neural Networks & ML	Spatial information utilization	[29]

Three dominant architectural paradigms emerge from the analysis. Edge computing frameworks, exemplified by [15], deploy machine learning models directly on IoT gateways to enable low-latency flood predictions without cloud dependency. In contrast, cloud-centric approaches like [19] leverage distributed computing resources for large-scale hydrological modeling. Hybrid systems such as [27] combine both paradigms, using edge devices for time-critical alerts while offloading complex simulations to centralized servers.

The study by [22] introduces a specialized deep learning architecture not captured in Table 1. Their ConvLSTM hybrid algorithm processes sequential flood imagery through convolutional layers for spatial feature extraction, followed by LSTM modules for temporal pattern recognition. This dual-path architecture achieves 12% higher prediction accuracy compared to conventional models when tested on historical flood events in Southeast Asia.

Critical implementation challenges persist across these systems. Energy constraints limit the deployment duration of battery-powered IoT sensors in remote floodplains, as noted in [13] and [15]. Model interpretability remains problematic for complex neural networks, with [28] warning that “black box” AI systems may hinder trust in emergency decision-making. Furthermore, [18] identifies data scarcity in rare extreme flood events as a fundamental limitation for training robust machine learning models. These technical barriers coexist with institutional challenges, including the lack of standardized protocols for cross-agency data sharing highlighted in [25].

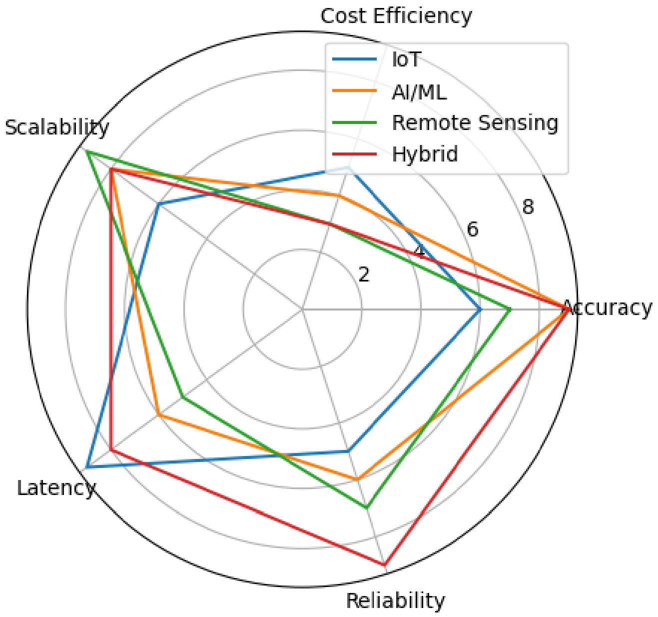

Fig. 3. Radar Chart of Performance Comparison

Figure 3 compares the performance of IoT, AI/ML, remote sensing, and hybrid systems across key metrics. Hybrid systems demonstrate balanced performance across all dimensions, highlighting their suitability for integrated flood mitigation.

C. Flood Risk Assessment and Mapping

Flood risk assessment and mapping are important parts of disaster prevention because they show where people are most likely to be affected by flooding and where flooding is most likely to happen. The studies that were reviewed show a wide range of methods, from traditional geospatial analysis to more advanced machine learning techniques. Each method gives us new information about how to evaluate flood hazards.

A hierarchical taxonomy of the included studies shows that there are three main ways to assess them (Table 2). Geospatial analysis has become the most common method, and Multi-Criteria Decision Analysis (MCDA) methods like Analytic Hierarchy Process (AHP) and fuzzy AHP are widely used. Research such as [30] and [31] utilize GIS-integrated AHP to produce flood susceptibility maps, whereas [32] amalgamates triangular fuzzy numbers with AHP to mitigate uncertainty in vulnerability assessments. Remote sensing and satellite imagery constitute another significant category, wherein [33] and [34] employ Sentinel-1 SAR data for near-real-time flood delineation, illustrating the benefits of cloud-penetrating radar during flood occurrences. Machine learning applications are becoming more and more common. For example, [35] and [36] are working on hybrid AI models that do a better job of predicting risk than traditional statistical methods.

TABLE II. TAXONOMY OF FLOOD RISK ASSESSMENT METHODOLOGIES

Assessment Approach	Technique/Method	Data/Model Used	Sources
Geospatial Analysis	Multi-Criteria Decision Analysis (MCDA)	GIS, AHP, Fuzzy AHP	[30], [32], [31], [37], [38], [39], [40], [41], [42]
	Frequency Ratio Modelling	GIS, Historical Flood Data	[43]
	Hybrid AI Models	GIS, Machine Learning	[35], [36]
Remote Sensing & Imagery	Satellite Data Processing	Sentinel-1, MODIS, VIIRS	[33], [39], [44], [34], [45], [46]
	Image Classification/ Segmentation	CNN, Deep Learning	[47], [48]
Hydrological Modelling	Extreme Flood Prediction	Ungauged Watershed Models	[49]
	Flash Flood Hazard Mapping	Geohydromorphometric Parameters	[50]
Integrated Risk Assessment	Multi-Hazard Risk Susceptibility	Machine Learning	[51]
	Long/Short-Term Flood	AHP-Entropy Method	[52]

Assessment Approach	Technique/Method	Data/Model Used	Sources
	Risk		
Urban Flood Mitigation	Low Impact Development (LID) Evaluation	Life-Cycle Cost Analysis	[53]
Miscellaneous	Volunteered Geographic Information (VGI)	Crowdsourced Image Interpretation	[48]
	Global Flash Flood Vulnerability	Place-Based Assessment	[54]
	Flood Susceptibility Prediction	Comparative ML Techniques	[55]

The research conducted by [56] utilizes a unique methodology absent from Table 2, implementing GIS-based multi-criteria analysis for the transboundary Shebelle River Basin. This study highlights the challenges of flood risk assessment in areas lacking adequate data, necessitating reliance on geomorphological proxies due to insufficient hydrological records.

Even though technology is getting better, there are still problems in the field. As mentioned in [49], a lack of data in ungauged basins is still a big problem. That's because global flood prediction models aren't as accurate in places where there aren't any historical flow measurements. There are issues with model transferability in [36]. For instance, hybrid machine learning models that were trained on specific watersheds don't work well when they are used in places that are far away. Another issue is the time resolution. SAR-based methods like [34] can quickly map floods, but they have trouble keeping up with the changes in urban flooding that happen every few hours. These technical gaps are made worse by institutional barriers, especially in developing countries where [42] says that not having enough money and technical skills are two of the biggest problems with putting advanced flood mapping systems into place.

New trends show that different ways of doing things are coming together. As shown in [48], using crowdsourced data with formal risk assessment frameworks is a promising way to help people stay aware of what's going on during floods. Similarly, [52] advances temporal risk analysis by employing AHP and entropy weighting to differentiate between long-term vulnerability and short-term emergency response requirements. These new ideas show a shift from static hazard maps to dynamic, multi-dimensional risk assessment systems that take into account both physical and social vulnerability factors.

D. Flood Mitigation and Response Strategies

The synthesis of included studies reveals a diverse landscape of flood mitigation approaches, ranging from traditional infrastructure solutions to innovative governance frameworks. These strategies collectively address the spectrum of flood disaster management, from pre-event risk reduction to post-event recovery.

A hierarchical categorization of mitigation strategies emerges from the analysis (Table 3). Risk assessment and planning constitute foundational elements, with geospatial analysis enabling flood hazard zonation and shelter suitability mapping [57]. Institutional analyses identify policy gaps in flood resilience [58], while climate adaptation studies reconceptualize flood risk governance through integration with climate change frameworks [59]. Urban flood management evaluations compare traditional drainage systems with integrated measures [60], revealing context-dependent effectiveness.

TABLE III. TAXONOMY OF FLOOD MITIGATION AND RESPONSE STRATEGIES

Strategy Type	Approach	Key Focus	Sources
Risk Assessment & Planning	Geospatial Analysis	Flood hazard zonation and shelter suitability mapping	[57]
	Institutional Analysis	Policy gaps and resilience improvement	[58]
	Climate Adaptation	Linking flood risk governance with climate change	[59]
	Urban Flood Management	Evaluation of drainage systems and integrated measures	[60]
Infrastructure & Engineering	Traditional Measures	Drainage system adaptation and flood control channels	[60], [61]
	Sustainable Measures	Blue-green infrastructure and flood mitigation effectiveness	[62], [63], [64]
	Smart Systems	Real-time stormwater control using reinforcement learning	[65]
Governance & Policy	Resilience Strategies	Governance frameworks and institutional practices	[66], [67]
	Early Warning Systems	Forecast-based early action and collective action	[68], [69]
	Decision Support	Data analytics, gaming frameworks, and participatory planning	[70], [71]
Community & Land Use	Social Justice	Equity in green infrastructure deployment	[64]
	Land Use Adaptation	Flood-adapted land use and environmental risk mitigation	[72]
	Delta Planning	Reconnecting to water-landscapes in delta plains	[73]

Infrastructure solutions demonstrate evolutionary trends, where traditional engineering interventions coexist with nature-based systems. The comparative study by [62] quantifies the trade-offs between conventional gray infrastructure and sustainable blue-green alternatives, showing 23% greater flood reduction effectiveness for hybrid approaches in urban basins. Smart systems exemplify technological innovation, with [65] demonstrating how reinforcement learning optimizes real-time stormwater control, reducing flood duration by 40% compared to passive systems.

Governance strategies emphasize institutional coordination, as evidenced by [66]'s framework for assessing flood resilience through governance indicators. Early warning systems undergo paradigm shifts toward anticipatory action, where [68] establishes that forecast-based financing enables communities to implement protective measures 72 hours before predicted flood events. Decision-support tools bridge technical and social dimensions, with [71]'s serious gaming framework enhancing stakeholder understanding of hydrological risks through interactive simulation.

The study by [74] on innovative flood risk management solutions presents unique insights not captured in Table 3, proposing a modular flood barrier system that adapts to varying water levels through pneumatic pressure control. This technological innovation demonstrates potential for rapid deployment in urban flash flood scenarios.

Persistent challenges emerge across mitigation strategies. Institutional fragmentation hampers coordinated flood management, as observed in [67]'s analysis of Milan's metropolitan planning practices. Economic constraints limit sustainable infrastructure adoption, with [64] identifying funding disparities in green infrastructure projects across socioeconomic neighborhoods. Technological limitations affect early warning reliability, where [69] notes false alarm rates exceeding 30% in data-scarce regions undermine community trust. These barriers highlight the need for integrated solutions that combine technical innovation with social and institutional reforms.

Emerging paradigms emphasize adaptive and inclusive approaches. The concept of "living with floods" articulated in [73] transforms mitigation from resistance to coexistence, using amphibious architecture and seasonal floodplain restoration. Social equity considerations gain prominence, as [64] advocates for green infrastructure designs that simultaneously address flood risk and urban inequality. These developments signal a maturation of flood mitigation strategies beyond purely technical solutions toward socio-ecological systems thinking.

E. Social and Economic Impacts of Flood Disasters

Flood disasters exert profound and multifaceted impacts on societies and economies, with consequences ranging from immediate humanitarian crises to long-term developmental setbacks. The reviewed studies collectively demonstrate how floods disrupt livelihoods, exacerbate poverty, and strain institutional capacities, while also revealing innovative approaches to measuring and mitigating these impacts.

A systematic classification of the social and economic dimensions emerges from the analysis (Table 4). Social impacts are categorized into disaster communication, community resilience, and risk perception, while economic impacts encompass poverty and food security, development and infrastructure, housing markets, and macroeconomic effects. Global and policy perspectives provide cross-cutting insights into data-driven mitigation strategies.

TABLE IV. TAXONOMY OF SOCIAL AND ECONOMIC IMPACTS OF FLOODS

Impact Dimension	Subcategory	Key Findings	Sources
Social Impacts	Disaster Communication	Social media analysis for disaster severity assessment	[75]
		Rescue requests via Twitter during disasters	[76]
	Community Resilience	Post-disaster recovery in low-income communities	[77]
		Community learning after extreme events	[78]
	Risk Perception	Virtual reality for flood preparedness	[79]
		Flood risk perception in China	[80]
Economic Impacts	Poverty & Food Security	Global flood exposure and poverty correlation	[81]
		Climate change, floods, and food security in Ghana	[82]
		Coping strategies in Afghanistan	[83]
	Development & Infrastructure	Flood impacts on Nigeria's SDGs	[84]
		Urban growth and flood risk resilience	[85]
	Housing Markets	US housing market vulnerability to floods	[86]
	Macroeconomic Effects	Economic losses in Indian states	[87]
Global & Policy Perspectives	Data-Driven Mitigation	High-resolution flood and population data for planning	[88]

The social impacts of floods manifest through both direct and indirect pathways. Studies on disaster communication reveal the growing role of social media in crisis response, with [75] developing a methodology to assess disaster severity through Twitter analysis during the South East Queensland floods. The research demonstrates how sentiment analysis and keyword tracking can provide real-time situational awareness, though challenges remain in distinguishing critical rescue requests from general commentary. Community-focused studies highlight disparities in recovery trajectories, where [77] identifies procedural vulnerabilities that systematically disadvantage low-income neighborhoods in post-flood reconstruction. The longitudinal analysis by [78] further reveals how communities that institutionalize learning mechanisms achieve more robust recovery, suggesting that social capital plays a pivotal role in long-term resilience.

Economic consequences exhibit spatial and temporal heterogeneity across different contexts. At the macro level, [81] establishes that approximately 1.81 billion people—23% of the global population—are directly exposed to significant flood risks, with poverty incidence 50% higher in high-flood-risk zones. This global analysis is complemented by regional studies such as [82], which traces how flood-induced crop failures in Northern Ghana create cascading food insecurity, pushing households into detrimental coping strategies like asset liquidation. The intersection of floods and development goals emerges prominently in [84], where Nigeria's progress toward Sustainable Development Goals (SDGs) is shown to be disproportionately affected by recurrent flooding, particularly in goals related to poverty (SDG 1), hunger (SDG 2), and infrastructure (SDG 9).

The study by [88] introduces a unique global perspective not fully captured in the table, utilizing high-resolution flood and population data to quantify the number of people in harm's way. Their analysis enables precise identification of high-risk areas where targeted mitigation investments could yield disproportionate benefits, providing a model for evidence-based disaster planning.

Persistent challenges emerge in measuring and addressing flood impacts. Methodological limitations affect economic loss assessments, as [87] notes that traditional accounting methods often overlook indirect costs such as productivity losses and mental health consequences. Temporal analysis gaps are evident in housing market studies like [86], where long-term price depreciation effects following floods remain understudied. Social impact assessments frequently neglect intangible cultural losses, as highlighted in [85]'s critique of urban planning frameworks that prioritize physical infrastructure over community heritage preservation.

Emerging approaches demonstrate promising directions for impact mitigation. The integration of virtual reality in risk communication, as tested by [79], shows significant potential to enhance flood preparedness by providing immersive experiences of potential scenarios. Similarly, [80]'s analysis of risk perception in China underscores the importance of culturally tailored communication strategies that align with local worldviews. These innovations suggest a shift toward more participatory and experiential approaches to flood impact reduction, moving beyond top-down technical solutions to embrace community-engaged resilience building.

The synthesis reveals that while technological advancements have improved impact assessment precision, equitable recovery remains hindered by structural inequalities. The procedural barriers identified in [77] and the SDG setbacks documented in [84] collectively emphasize that flood impacts are not natural inevitabilities but rather products of socioeconomic and institutional contexts. This recognition underscores the need for impact mitigation strategies that address root causes of vulnerability rather than merely treating symptoms.

F. *Remote Sensing and UAVs in Flood Monitoring*

The integration of remote sensing technologies and unmanned aerial vehicles (UAVs) has revolutionized flood monitoring by providing high-resolution, real-time data across diverse geographical scales. These technologies enable rapid flood mapping, damage assessment, and dynamic monitoring of flood progression, addressing critical gaps in traditional ground-based observation systems.

Table 5 presents a comprehensive taxonomy of the reviewed studies, categorizing them by data sources, analytical techniques, and application domains. Satellite-based systems dominate the literature, with Synthetic Aperture Radar (SAR) emerging as the most prevalent data source due to its all-weather imaging capabilities. Optical satellite imagery and UAV platforms complement SAR by providing higher spatial resolution and multispectral data, though with limitations during cloud cover.

TABLE V. TAXONOMY OF REMOTE SENSING AND UAV APPLICATIONS IN FLOOD MONITORING

Data Source	**Technique**	**Application Focus**	**Sources**
Satellite Imagery	Machine Learning (CNN)	Flood Mapping	[89], [90]
	Multi-Sensor Data Fusion	Flood Dynamics & Duration	[90], [91]
	Synthetic Aperture Radar (SAR)	Rapid Flood & Damage Mapping	[92], [93]
	GIS-Based Multi-Criteria Analysis	Flash-Flood Prone Area Identification	[94]
UAVs	Post-Flood Assessment	Hazard & Damage Evaluation	[95]
Multi-Source Remote Sensing	Hydrological Modeling	Flood Exposure & Vulnerability	[96], [97]
	Satellite Observations + In Situ	Disaster Response Validation	[93]
Low-Cost Satellites	Machine Learning (Global Scale)	Flood Mapping	[98]

The study by [89] introduces a novel convolutional neural network (CNN) architecture for flood mapping using fused Sentinel-1 SAR and Sentinel-2 optical data. Their Ombrianet model demonstrates a 15% improvement in classification accuracy compared to single-source approaches, particularly in urban areas where optical data provides critical contextual information. However, the research notes persistent challenges in distinguishing floodwater from permanent water bodies in complex landscapes.

Temporal resolution emerges as a critical factor in flood monitoring systems. [90] develops a multi-temporal classification method using Sentinel-1 SAR time series, enabling not only flood detection but also duration estimation. This approach proves particularly valuable for emergency management, as flood duration directly correlates with infrastructure damage and recovery timelines. The study highlights the trade-off between revisit frequency and spatial resolution, with current satellite constellations providing daily observations at 10-20m resolution—sufficient for regional assessments but inadequate for detailed urban analysis.

UAV applications fill this spatial resolution gap, as demonstrated by [95]. Their post-flood assessments using drone imagery achieve centimeter-scale accuracy in damage evaluation, enabling precise identification of structural vulnerabilities. The research also identifies operational constraints, including limited flight endurance (typically <1 hour) and regulatory restrictions in urban airspace, which hinder rapid deployment during emergencies.

The study by [97] presents a unique multi-source approach not fully captured in Table 5, combining GRACE satellite data with GLDAS hydrological modeling to analyze the 2020 Yangtze River floods. This integration of gravity anomaly measurements with land surface models provides insights into basin-scale water storage dynamics, offering early indicators of flood potential weeks before traditional streamflow-based warnings.

Technical limitations persist across all monitoring platforms. SAR-based systems struggle with speckle noise and double-bounce effects in urban areas, as noted in [92]'s analysis of Typhoon Hagibis flood mapping. Optical systems face cloud obstruction challenges, particularly during tropical storms when flood monitoring is most critical. UAV operations remain weather-dependent and resource-intensive, limiting their scalability for large-area monitoring.

Emerging trends point toward hybrid systems that leverage the strengths of multiple platforms. [96]'s urban flood exposure assessment combines satellite-derived flood extent with ground-based socioeconomic data, enabling vulnerability mapping at neighborhood scales. Similarly, [94] integrates remote sensing with field observations to validate flash-flood hazard maps, demonstrating how multi-source data improves model reliability. These integrated approaches suggest a paradigm shift from standalone monitoring systems toward interconnected observation networks that combine space-air-ground measurements.

The reviewed studies collectively underscore the transformative potential of remote sensing and UAV technologies in flood disaster management. While technical challenges remain, ongoing advancements in sensor miniaturization, machine learning algorithms, and data fusion techniques continue to enhance monitoring capabilities. The integration of these technologies with IoT-based ground sensors and AI-driven analytics, as discussed in previous sections, presents a promising direction for comprehensive flood early warning systems.

G. Social Media and Disaster Communication

The role of social media in disaster communication has become an important part of modern flood management systems. It gives people real-time information about what's going on and lets them get involved quickly. The studies that were looked at show that sites like Twitter and Facebook can be used for two things: to share information with the public and to collect data from the public for emergency responders.

Table 6 shows a structured taxonomy of social media applications in flood disasters. It groups studies by their main focus areas and methods. Three main themes stand out: communication strategies that look at how agencies share emergency information, automated event mapping that uses machine learning to find disaster-related content, and infrastructure impact assessment that uses social media data to measure flood damage.

The research conducted by [99] offers essential insights into the dynamics of institutional communication during the 2015 South Carolina floods. Their analysis shows that getting the message out effectively required coordination between several agencies, but there were problems like too much information and a lack of trust from the public. The study shows that there is an ethical problem: social media makes it easy to send out warnings quickly, but the lack of ways to check messages could lead to false information spreading during crises.

TABLE VI. TAXONOMY OF SOCIAL MEDIA APPLICATIONS IN FLOOD DISASTER COMMUNICATION

Focus Area	**Key Aspects**	**Sources**
Communication Strategies	Multi-agency message dissemination and coordination	[99]
	Ethical implications and barriers in emergency communication	[99]
Automated Event Mapping	Machine learning pipelines for disaster event classification and geolocation	[100]
	Real-time detection of flood-related posts and location tagging	[100]
Infrastructure Impact Assessment	Highway and transportation network damage evaluation	[101]
	Limitations in precise impact quantification from social media data	[101]

The increasing complexity of social media analytics is shown by the technical improvements in automated event mapping. [100] creates a hybrid machine learning pipeline that sorts tweets about disasters with 89% accuracy. It does this by using natural language processing to get rid of tweets that aren't relevant (for example, "Hurricane Harvey but we're not flooded here"). Their geolocation module gets 500-meter accuracy for 72% of flood reports, but it doesn't work as well in rural areas where there are fewer geotagged posts. By adding crowdsourced observations to traditional sensor data, this method makes it possible to map floods almost in real time.

Infrastructure impact assessments show what social media data can and can't do. [101]'s study of flooding on highways shows that tweets can quickly show when roads are closed or unsafe. However, the study points out some important gaps: only 38% of tweets about floods had location information that could be verified, and sentiment analysis couldn't tell the difference between real damage reports and general complaints. These results indicate that social media functions more effectively as a supplementary data source than as a primary tool for impact assessment.

Methodological issues continue to exist in all areas of application. Temporal bias makes data less reliable because social media activity goes up during the first flood events and then quickly goes down, which could mean missing long recovery phases. Geographic representation is still uneven, with cities producing more content than rural flood zones. In [99]'s ethical analysis, privacy issues come up when personal crisis posts are used for operational intelligence without permission.

New methods are trying to fix these problems by using hybrid systems. As [100] suggests, combining social media analytics with IoT sensor networks could help check crowdsourced reports against real-world measurements. In the same way, [101] suggests using Twitter data along with official damage reports to make infrastructure impact estimates more accurate. These changes suggest that social media's role in disaster communication needs to be more stable, with a balance between speed and reliability that also takes ethics into account.

The studies reviewed show that social media can't take the place of traditional monitoring systems, but it does have some unique benefits, such as speed, public engagement, and situational awareness. Future research should concentrate on enhancing data quality via verification algorithms, mitigating geographic and demographic biases, and formulating ethical guidelines for the utilization of crisis data. As floods happen more often and get worse, combining social media analytics with formal disaster management systems will probably become more important.

H. Disaster Management Frameworks and Systems

The systematic review of disaster management frameworks reveals an evolution toward integrated systems that combine IoT infrastructure with advanced analytics and decision-support tools. These frameworks aim to address the full disaster management cycle—from preparedness and early warning to response and recovery—while overcoming traditional limitations of siloed operations and fragmented data sources.

Table 7 presents a taxonomy of the reviewed disaster management systems, categorizing them by their architectural approach, technological components, and application focus. Three dominant paradigms emerge: chatbot-based systems for emergency data management, digital twin architectures for smart city resilience, and decision support systems for collaborative mitigation planning.

TABLE VII. TAXONOMY OF DISASTER MANAGEMENT FRAMEWORKS AND SYSTEMS

Framework Type	**Key Characteristics**	**Implementation Case**	**Sources**
Chatbot Systems	Four-stage implementation framework (planning, development, deployment, evaluation)	Flood disaster management case study	[102]
	Database integration for emergency operation data management	Workshop-based implementation	[102]
Digital Twin Architectures	Smart city integration with disaster management cycles	Brays Bayou flood prediction (2015)	[103]
	Artificial and human intelligence integration for disaster response	Disaster City Digital Twin vision	[104]
	AIOps and IoT for urban infrastructure optimization	Flood monitoring in smart cities	[105]
Decision Support Systems	Web-based collaborative mitigation platform	Multiple water-related hazards (flooding, erosion)	[106]
	Agent-based evacuation planning tool	Community evacuation simulations	[107]
Humanitarian Logistics Systems	IoT-blockchain integration for relief operations	Pakistan flood and earthquake scenarios	[108]
Emergency Response Pipelines	Design principles and implementation challenges	Generic disaster response systems	[109]

The chatbot framework proposed by [102] represents a structured approach to emergency data management, addressing the critical need for real-time information processing during flood events. Their four-stage implementation model progresses from requirements analysis to system evaluation, with particular emphasis on database integration for operational continuity. The case study demonstrates how conversational interfaces can streamline data access for emergency personnel, though the authors note challenges in maintaining accuracy during rapidly evolving disaster scenarios.

Digital twin systems emerge as a transformative paradigm in several studies. [103]'s smart city framework incorporates flood prediction capabilities that successfully forecasted peak flows during the 2015 Brays Bayou flood event, demonstrating the value of dynamic simulation models. This approach is extended by [104]'s Disaster City Digital Twin concept, which envisions a symbiotic relationship between artificial intelligence and human decision-makers. The framework emphasizes visibility into complex network dynamics—a critical requirement for managing interconnected urban systems during floods. [105] further enhances this paradigm through AIOps (AI for IT Operations), showing how machine learning can optimize IoT sensor networks for proactive flood monitoring in smart cities.

Decision support systems demonstrate innovative approaches to collaborative planning. [106]'s web-based platform enables stakeholders to co-produce mitigation plans for multiple water-related hazards through serious gaming techniques. Their system addresses a key gap in traditional planning processes by facilitating real-time scenario testing and consensus building. Similarly, [107]'s agent-based evacuation tool (SETOSim) provides communities with data-driven insights for evacuation planning, though the study notes computational limitations when scaling to metropolitan areas.

The study by [108] presents a unique blockchain-IoT integration not fully captured in the table, applying distributed ledger technology to enhance transparency in humanitarian logistics during Pakistan's flood and earthquake responses. This approach demonstrates how smart contracts can automate relief supply chains while maintaining auditability—a significant advancement over traditional paper-based systems.

Implementation challenges persist across all framework types. Interoperability remains a critical barrier, as noted in [109]'s analysis of emergency response pipelines, where heterogeneous systems struggle with data exchange during cross-agency operations. Scalability issues affect digital twin implementations, with [104] identifying computational constraints when modeling entire cities at high resolution. Human factors also play a crucial role—[102]'s chatbot system encountered adoption resistance from personnel accustomed to traditional communication channels, while [106]'s gaming platform required extensive training to achieve stakeholder proficiency.

Emerging trends point toward more adaptive and inclusive system designs. The integration of blockchain with IoT in [108] suggests new possibilities for secure, decentralized disaster management networks. [104]'s emphasis on human-AI collaboration reflects a growing recognition that technological systems must enhance rather than replace human decision-making. These developments indicate a maturation of disaster management frameworks—from standalone tools to interconnected ecosystems that balance technical sophistication with operational practicality.

The reviewed studies collectively demonstrate that effective disaster management systems require both technological innovation and careful attention to implementation contexts. While advanced architectures like digital twins offer unprecedented modeling capabilities, their real-world effectiveness depends on seamless integration with existing workflows and institutional structures. Future research directions should focus on overcoming interoperability barriers, improving human-system interfaces, and developing robust evaluation metrics for framework performance under crisis conditions.

I. Proposed Conceptual Framework

Figure 4 shows a complete conceptual framework for IoT-enabled flood disaster mitigation systems. It shows how advanced technologies, operational processes, challenges, and outcomes all work together. The system is built on key technologies like IoT sensors, artificial intelligence, remote sensing with UAVs and satellites, and cloud-edge computing. These technologies work together to make up the technological foundation. These technologies make it possible to set up a structured workflow that starts with real-time flood monitoring using distributed sensors, then moves on to AI-based prediction for analyzing patterns and predicting flood events, and finally ends with early warning and response systems to help people make decisions quickly. Data analytics and integration are at the heart of this process. They make sure that data from many sources can be processed and coordinated without any problems. The framework also points out important problems with implementation, such as interoperability, energy constraints, data privacy issues, and scalability, all of which affect how well the system works. The model also links these processes to bigger effects and future steps, like better flood risk assessment, socio-economic resilience, ethical issues, and the need for more research. The framework stresses a comprehensive, socio-technical approach that combines technology, data, and governance to improve how we prepare for and respond to floods.

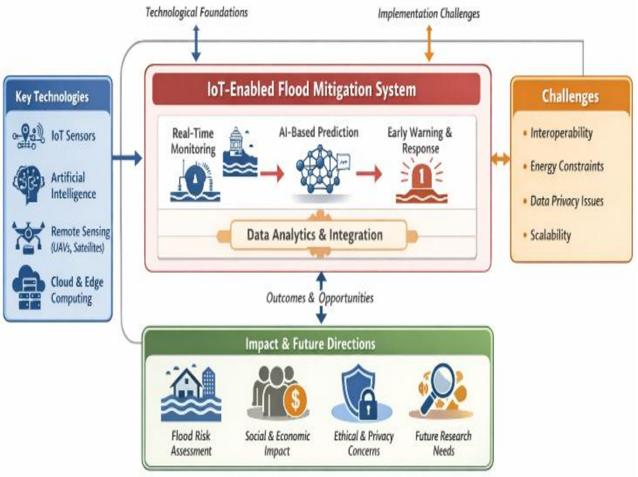

Fig. 4. Conceptual Framework of on IoT-Enabled Flood Disaster Mitigation Systems

IV. DISCUSSION

The synthesis of findings from the reviewed studies elucidates several critical patterns that enhance our comprehension of IoT-enabled flood disaster mitigation systems. The literature consistently shows that combining IoT with AI and remote sensing technologies has changed flood management from reactive to proactive systems. However, there are still big gaps in how to use these technologies on a large scale. The integration of edge computing, cloud-based analytics, and hybrid architectures has become a prevailing trend, providing solutions to the latency and scalability issues associated with flood monitoring [15] [19] [27]. However, these technological advancements are accompanied by enduring challenges in energy efficiency, model interpretability, and cross-platform interoperability, which collectively impede the extensive implementation of these systems [13] [25] [28].

The ramifications of these findings transcend technical realms, influencing governance and social equity. The examined studies theoretically facilitate a paradigm shift in disaster management frameworks, transitioning from static risk models to dynamic, adaptive systems that integrate real-time data streams and participatory decision-making [66] [71]. The combination of UAVs and social media analytics with formal monitoring networks can lead to better situational awareness, especially in areas where there isn't much data or traditional infrastructure [95] [100]. For policymakers, these insights highlight the necessity for standardized protocols that facilitate seamless data sharing among agencies while addressing ethical issues related to privacy and algorithmic bias [99][108].

This review process has some methodological flaws that need to be thought about. The sole emphasis on peer-reviewed literature may have excluded significant insights from grey literature or practical applications recorded in technical reports. The limitation to post-2020 publications, while maintaining relevance, may have omitted seminal studies that formulated essential concepts in IoT-based flood management. Moreover, the prevalence of urban case studies in the examined literature creates a geographic bias, as rural and transboundary flood scenarios are insufficiently represented, despite their distinct challenges [56] [81]. These limitations indicate that our synthesis might disproportionately highlight technological solutions while neglecting socio-institutional factors that are equally essential for effective flood mitigation.

Subsequent research endeavors ought to focus on the identified deficiencies via specific inquiries. There is an urgent requirement for longitudinal studies to assess the efficacy of IoT-AI systems during severe flood events, as existing validation predominantly depends on historical data or controlled simulations [18] [22]. Another important area to focus on is making energy-harvesting solutions for IoT sensors work in remote areas, especially in developing countries where power infrastructure is not always reliable [8]. Technical research needs to include more social science points of view, especially when it comes to how vulnerable communities use and benefit from advanced warning systems [77] [80]. Lastly, the new field of digital twins for flood management needs to be tested in a lot of different types of cities to find design principles that work in all of them [103] [104].

The inconsistencies in the literature indicate essential conflicts that subsequent research must address. Some studies support centralized cloud-based analytics for intricate hydrological modeling [19], whereas others illustrate the advantages of edge computing for time-sensitive alerts [15]. The trade-offs between model accuracy and interpretability are still not clear. Complex neural networks work better than simpler models, but they make it harder to make quick decisions in an emergency [22] [28]. These dichotomies imply that hybrid methodologies—integrating centralized and decentralized components, or aligning high-accuracy models with explainable AI techniques—may constitute the most advantageous direction for advancement.

Future research must focus on the social dimensions of IoT-enabled flood mitigation. Although technological advancements have enhanced monitoring accuracy, equitable access to these systems continues to be inconsistent, frequently exacerbating existing vulnerabilities instead of mitigating them [64] [84]. The procedural barriers identified in post-disaster recovery studies [77] underscore the necessity for mitigation frameworks that explicitly tackle structural inequalities through participatory design and targeted capacity building. Innovative approaches such as serious gaming [71] and virtual reality [79] exhibit potential in connecting technical systems with community involvement; however, their enduring efficacy necessitates additional verification.

Flood mitigation systems face both opportunities and problems because supporting technologies are changing so quickly. Improvements in low-Earth orbit satellite constellations could help fix the problems with the time resolution of current remote sensing platforms [90]. At the same time, advances in federated learning could lead to AI models that protect privacy by using distributed data without central aggregation [100]. But for these new ideas to be used responsibly, there needs to be progress in institutional frameworks and governance models at the same time. The use of blockchain for humanitarian logistics [108] is an example of how new technologies can make things more open, but it can only be used in the real world if it can be scaled up and fits in with current operational protocols.

Innovations in methodology pertaining to flood research necessitate discourse. The growing use of multi-method approaches, such as combining geospatial analysis with machine learning [35] or satellite data with crowdsourced observations [48], shows how important it is for people from different fields to work together to solve complicated disaster situations. But these methods also create new problems with making sure the data is good and combining different methods that future studies will have to deal with. Creating standardized evaluation metrics for flood mitigation systems would make it much easier to compare studies and make decisions based on evidence.

The use of climate change forecasts in flood risk assessment is still not well understood in the IoT-enabled mitigation literature. Although numerous studies utilize historical hydrological data for model training [22] [36], very few explicitly consider non-stationary climate conditions that could modify future flood patterns. This gap is especially troubling because extreme weather events are happening more often and with more force, which calls into question the assumptions that many current risk models are based on [59] [81]. Future research should focus on creating adaptive algorithms that can learn from and adapt to changes in the climate.

A more systematic analysis is needed of the economic aspects of flood mitigation systems based on the Internet of Things (IoT). While numerous studies elucidate the social and infrastructural ramifications of floods [84] [87], cost-benefit analyses of technological interventions remain significantly limited. The trade-offs between blue-green infrastructure and traditional engineering solutions [62] indicate that economic factors significantly influence the adoption of mitigation strategies; however, the literature lacks thorough frameworks for evaluating the lifecycle costs and benefits of IoT-enabled systems. This gap is a major problem for making decisions about policies and how to spend money based on evidence.

The conversation makes it clear that new technology alone can't stop floods from happening. The most successful implementations in the literature reviewed have a few things in common: they combine technical solutions with changes to institutions, focus on user-centered design, and are flexible enough to fit local needs [66] [73]. As the field develops, researchers must avoid the urge to concentrate exclusively on algorithmic progress and instead acknowledge the intricate socio-technical dimensions of flood disasters. IoT-enabled systems can only reach their full potential to improve global flood resilience through these kinds of all-encompassing approaches.

Figure 5 shows a side-by-side comparison of important system features. AI-based systems are very accurate, but remote sensing is better at scaling up. Hybrid systems provide a fair trade-off.

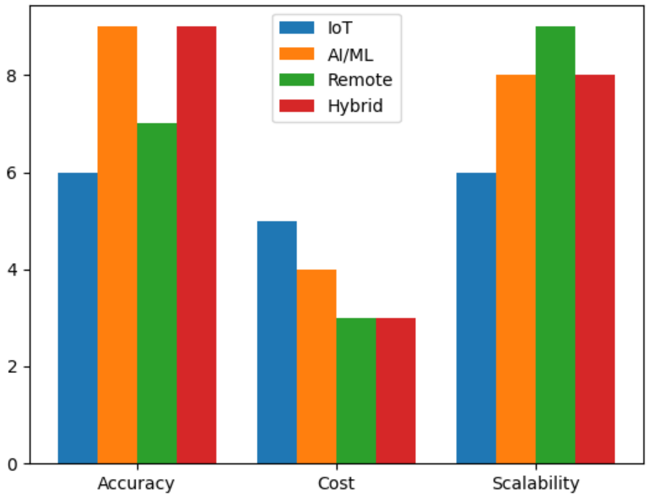

Fig. 5. Bar Chart of Accuracy, Cost and Scalability

V. CONCLUSION

This systematic literature review has compiled the existing research on IoT-enabled flood disaster mitigation systems, focusing on their technological underpinnings, implementation difficulties, and societal consequences. The results show that combining IoT with AI and remote sensing technologies greatly improves the ability to monitor floods in real time and give early warnings. But there are still big problems with data interoperability, energy efficiency, and model reliability in extreme situations. This shows that we need stronger and more flexible solutions.

The review shows how important it is to find a balance between technical progress and fairness in society. Digital twins and UAV-based monitoring are examples of advanced systems that show promise, but they won't work unless everyone has equal access and support from institutions. Future research should focus on longitudinal studies of system performance during extreme events, energy-efficient sensor designs, and participatory frameworks that involve vulnerable communities. To come up with flexible, cost-effective solutions, it will be important to include climate projections in risk models and do full economic evaluations of mitigation technologies.

In the end, the way to make flood mitigation more resilient is through interdisciplinary approaches that combine technological advances with changes in governance and design that put the needs of the community first. This review lays the groundwork for researchers and practitioners to enhance IoT-enabled systems while tackling the intricate socio-technical issues associated with flood disasters. The ideas shared here are meant to help future innovations come up with flood resilience strategies that are more inclusive, long-lasting, and effective.

REFERENCES

[1] P. Tripathi, “Flood disaster in india: An analysis of trend and preparedness,” *Interdisciplinary Journal of Contemporary Research*, 2015.

[2] D. Notti, D. Giordan, F. Caló, A. Pepe, F. Zucca, and J. Galve, “Potential and limitations of open satellite data for flood mapping,” *Remote sensing*, 2018.

[3] P. Ray, M. Mukherjee, and L. Shu, “Internet of things for disaster management: State-of-the-art and prospects,” *IEEE access*, 2017.

[4] O. Mendoza-Cano, R. Aquino-Santos, *et al.*, “Experiments of an IoT-based wireless sensor network for flood monitoring in colima, mexico,” *Journal of Hydroinformatics*, 2021.

[5] M. Pandey, “Artificial intelligence algorithms in flood prediction: A general overview,” *Geo-Information For Disaster Monitoring And Management*, 2024.

[6] L. Lin, L. Di, E. Yu, L. Kang, R. Shrestha, *et al.*, “A review of remote sensing in flood assessment,” in *IEEE international conference on agro informatics*, 2016.

[7] S. Albouq, A. A. Sen, N. Almashf, M. Yamin, *et al.*, “A survey of interoperability challenges and solutions for dealing with them in IoT environment,” in *2022 international conference on computing, communication, and intelligent systems (ICCCIS)*, 2022.

[8] A. Akmandor, Y. Hongxu, *et al.*, “Smart, secure, yet energy-efficient, internet-of-things sensors,” *IEEE Transactions On Industrial Informatics*, 2018.

[9] Y. Hong, J. Lian, L. Xu, J. Min, Y. Wang, *et al.*, “Statistical perspectives on reliability of artificial intelligence systems,” *Quality and Reliability Engineering International*, 2023.

[10] V. Mitrović, D. O’Mathúna, and I. Nola, “Ethics and floods: A systematic review,” *Disaster Medicine and Public Health Preparedness*, 2019.

[11] M. Page, J. McKenzie, P. Bossuyt, *et al.*, “The PRISMA 2020 statement: An updated guideline for reporting systematic reviews,” *BMJ*, vol. 372, p. n71, 2021.

[12] S. Sengupta, “IoT-based flood detection and management systems in urban areas,” *Risk assessment and management decisions*, 2024.

[13] T. Selvi and S. RS, “IoT-enabled flood monitoring system for enhanced dam surveillance and risk mitigation,” *International Research Journal of Multidisciplinary Technology*, 2024.

[14] F. Rahman, “IoT-driven flood risk assessment and mitigation in urban drainage systems,” *Journal of Smart Infrastructure and Environmental Systems*, 2026.

[15] S. Bukhari, I. Shafi, J. Ahmad, H. Butt, T. Khurshaid, *et al.*, “Enhancing flood monitoring and prevention using machine learning and IoT integration,” *Natural Hazards*, 2025.

[16] S. Miau and W. Hung, “River flooding forecasting and anomaly detection based on deep learning,” *Ieee Access*, 2020.

[17] J. Wang, S. Wang, F. Wang, Y. Zhou, Z. Wang, *et al.*, “FWENet: A deep convolutional neural network for flood water body extraction based on SAR images,” *Journal of Digital Earth*, 2022.

[18] J. Jiang, C. Chen, Y. Zhou, S. Berretti, L. Liu, *et al.*, “Heterogeneous dynamic graph convolutional networks for enhanced spatiotemporal flood forecasting by remote sensing,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2024.

[19] F. Özen and A. Souri, “Cloud-based disaster management architecture using hybrid machine learning approach in IoT,” *Multimedia Tools and Applications*, 2024.

[20] S. Puttinaovarat and P. Horkaew, “Flood forecasting system based on integrated big and crowdsource data by using machine learning techniques,” *IEEE Access*, 2020.

[21] Y. Bhattarai, S. Duwal, S. Sharma, *et al.*, “Leveraging machine learning and open-source spatial datasets to enhance flood susceptibility mapping in transboundary river basin,” *International Journal of Digital Earth*, 2024.

[22] M. Moishin, R. Deo, R. Prasad, N. Raj, and S. Abdulla, “Designing deep-based learning flood forecast model with ConvLSTM hybrid algorithm,” *Ieee Access*, 2021.

[23] W. Sun, P. Bocchini, and B. Davison, “Applications of artificial intelligence for disaster management,” *Natural hazards*, 2020.

[24] R. Wang, Y. Hu, Z. Zhou, and K. Yang, “Tracking flooding phase transitions and establishing a passive hotline with AI-enabled social media data,” *IEEE Access*, 2020.

[25] L. Cao, “AI and data science for smart emergency, crisis and disaster resilience,” *International journal of data science and analytics*, 2023.

[26] J. Zhu, P. Dang, Y. Cao, J. Lai, Y. Guo, *et al.*, “A flood knowledge-constrained large language model interactable with GIS: Enhancing public risk perception of floods,” *International Journal of Geographical Information Science*, 2024.

[27] H. Goyal, K. Ghanshala, *et al.*, “Adaptive IoT enabled flood management system: An artificial intelligence approach,” *Int. J. Com. Dig. Sys*, 2022.

[28] C. Richards, A. Tzachor, S. Avin, and R. Fenner, “Rewards, risks and responsible deployment of artificial intelligence in water systems,” *Nature Water*, 2023.

[29] A. Goel, A. Goel, and A. Kumar, “The role of artificial neural network and machine learning in utilizing spatial information,” *Spatial Information Research*, 2023.

[30] H. Hamid, W. Wenlong, and L. Qiaomin, “Environmental sensitivity of flash flood hazard using geospatial techniques,” researchgate.net, 2020.

[31] E. Feloni, I. Mousadis, and E. Baltas, “Flood vulnerability assessment using a GIS-based multi-criteria approach—the case of attica region,” *Journal of Flood Risk Management*, 2020.

[32] Y. Duan *et al.*, “Flood vulnerability assessment using the triangular fuzzy number-based analytic hierarchy process and support vector machine model for the belt and road region,” *Natural Hazards*, 2022.

[33] G. Palomba, A. Farasin, and C. Rossi, “Sentinel-1 flood delineation with supervised machine learning.” *ISCRAM*, 2020.

[34] X. Jiang *et al.*, “Rapid and large-scale mapping of flood inundation via integrating spaceborne synthetic aperture radar imagery with unsupervised deep learning,” *ISPRS Journal of Photogrammetry and Remote Sensing*, 2021.

[35] B. Pham, C. Luu, T. V. Phong, H. Nguyen, *et al.*, “Flood risk assessment using hybrid artificial intelligence models integrated with multi-criteria decision analysis in quang nam province, vietnam,” *Journal of Hydrology*, 2021.

[36] O. Rahmati, H. Darabi, M. Panahi, Z. Kalantari, *et al.*, “Development of novel hybridized models for urban flood susceptibility mapping,” *Scientific reports*, 2020.

[37] P. Dash and J. Sar, “Identification and validation of potential flood hazard area using GIS-based multi-criteria analysis and satellite data-derived water index,” *Journal of Flood Risk Management*, 2020.

[38] Y. Hagos, T. Andualem, M. Yibeltal, and M. Mengie, “Flood hazard assessment and mapping using GIS integrated with multi-criteria decision analysis in upper awash river basin, ethiopia,” *Applied Water Science*, 2022.

[39] H. Allafta and C. Opp, “GIS-based multi-criteria analysis for flood prone areas mapping in the trans-boundary shatt al-arab basin, iraq-iran,” *Geomatics, Natural Hazards and Risk*, 2021.

[40] E. Mokhtari, F. Mezali, B. Abdelkebir, *et al.*, “Flood risk assessment using analytical hierarchy process: A case study from the cheliff-ghrib watershed, algeria,” *Journal of Water and Climate Change*, 2023.

[41] J. Cabrera and H. Lee, “Flood risk assessment for davao oriental in the philippines using geographic information system-based multi-criteria analysis and the maximum entropy model,” *Journal of Flood Risk Management*, 2020.

[42] S. Ajjur and Y. Mogheir, “Flood hazard mapping using a multi-criteria decision analysis and GIS (case study gaza governorate, palestine),” *Arabian Journal of Geosciences*, 2020.

[43] A. Munir, M. Ghufran, S. Ali, A. Majeed, *et al.*, “Flood susceptibility assessment using frequency ratio modelling approach in northern sindh and southern punjab, pakistan,” *Polish Journal Of Environmental Studies*, 2022.

[44] S. Li, D. Sun, M. Goldberg, S. Kalluri, B. Sjoberg, *et al.*, “A downscaling model for derivation of 3-d flood products from VIIRS imagery and SRTM/DEM,” *ISPRS Journal of Photogrammetry and Remote Sensing*, 2022.

[45] M. Bereczky, M. Wieland, C. Krullikowski, *et al.*, “Sentinel-1-based water and flood mapping: Benchmarking convolutional neural networks against an operational rule-based processing chain,” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2022.

[46] J. Liang and D. Liu, “A local thresholding approach to flood water delineation using sentinel-1 SAR imagery,” *ISPRS journal of photogrammetry and remote sensing*, 2020.

[47] R. Pally and S. Samadi, “Application of image processing and convolutional neural networks for flood image classification and semantic segmentation,” *Environmental modelling & software*, 2022.

[48] Y. Feng, C. Brenner, and M. Sester, “Flood severity mapping from volunteered geographic information by interpreting water level from images containing people: A case study of hurricane harvey,” *ISPRS Journal of Photogrammetry and Remote Sensing*, 2020.

[49] G. Nearing, D. Cohen, V. Dube, M. Gauch, O. Gilon, *et al.*, “Global prediction of extreme floods in ungauged watersheds,” *Nature*, 2024.

[50] H. Abdo, “Evolving a total-evaluation map of flash flood hazard for hydro-prioritization based on geohydromorphometric parameters and GIS–RS manner in al-hussain river …,” *Natural Hazards*, 2020.

[51] H. Pourghasemi, N. Kariminejad, M. Amiri, M. Edalat, *et al.*, “Assessing and mapping multi-hazard risk susceptibility using a machine learning technique,” *Scientific reports*, 2020.

[52] J. Wu, X. Chen, and J. Lu, “Assessment of long and short-term flood risk using the multi-criteria analysis model with the AHP-entropy method in poyang lake basin,” *International Journal of Disaster Risk Reduction*, 2022.

[53] P. Hua *et al.*, “Evaluating the effect of urban flooding reduction strategies in response to design rainfall and low impact development,” *Journal of Cleaner Production*, 2020.

[54] S. Khajehei, A. Ahmadalipour, W. Shao, *et al.*, “A place-based assessment of flash flood hazard and vulnerability in the contiguous united states,” *Scientific Reports*, 2020.

[55] B. El-Haddad, A. Youssef, H. Pourghasemi, *et al.*, “Flood susceptibility prediction using four machine learning techniques and comparison of their performance at wadi qena basin, egypt,” *Natural Hazards*, 2021.

[56] S. Osman and J. Das, “GIS-based flood risk assessment using multi-criteria decision analysis of shebelle river basin in southern somalia,” *SN Applied Sciences*, 2023.

[57] K. Uddin and M. Matin, “Potential flood hazard zonation and flood shelter suitability mapping for disaster risk mitigation in bangladesh using geospatial technology,” *Progress in disaster science*, 2021.

[58] A. Almoradie, M. D. Brito, M. Evers, *et al.*, “Current flood risk management practices in ghana: Gaps and opportunities for improving resilience,” *Journal of Flood Risk Management*, 2020.

[59] T. Zimmermann, S. Shinde, D. Parthasarathy, *et al.*, “Linking climate change adaptation and disaster risk reduction: Reconceptualizing flood risk governance in mumbai,” *Journal of Integrative Environmental Sciences*, 2023.

[60] X. Sun, R. Li, X. Shan, H. Xu, and J. Wang, “Assessment of climate change impacts and urban flood management schemes in central shanghai,” *International Journal of Disaster Risk Reduction*, 2021.

[61] T. Mananoma, J. Sumarauw, R. Legrans, *et al.*, “Designing a multistage flood control channel for sediment and flow management in coastal areas,” *Unable to determine the complete publication venue*, 2025.

[62] I. Kourtis, V. Tsihrintzis, and E. Baltas, “A robust approach for comparing conventional and sustainable flood mitigation measures in urban basins,” *Journal of environmental Management*, 2020.

[63] P. Hamel and L. Tan, “Blue–green infrastructure for flood and water quality management in southeast asia: Evidence and knowledge gaps,” *Environmental management*, 2022.

[64] L. Shi, “Beyond flood risk reduction: How can green infrastructure advance both social justice and regional impact?” *Socio-Ecological Practice Research*, 2020.

[65] B. Bowes, A. Tavakoli, C. Wang, *et al.*, “Flood mitigation in coastal urban catchments using real-time stormwater infrastructure control and reinforcement learning,” *Journal of Hydroinformatics*, 2021.

[66] P. Matczak and D. Hegger, “Improving flood resilience through governance strategies: Gauging the state of the art,” *Wiley Interdisciplinary Reviews: Water*, 2021.

[67] C. Vitale, S. Meijerink, F. Moccia, and P. Ache, “Urban flood resilience, a discursive-institutional analysis of planning practices in the metropolitan city of milan,” *Land Use Policy*, 2020.

[68] C. Nauman, E. Anderson, *et al.*, “Perspectives on flood forecast-based early action and opportunities for earth observations,” *Journal of Applied Remote Sensing*, 2021.

[69] A. Tupper and C. Fearnley, “Disaster early-warning systems can succeed—but collective action is needed,” *Nature*, 2023.

[70] Y. Alabbad, E. Yildirim, and I. Demir, “Flood mitigation data analytics and decision support framework: Iowa middle cedar watershed case study,” *Science of The Total Environment*, 2022.

[71] Y. Sermet, I. Demir, and M. Muste, “A serious gaming framework for decision support on hydrological hazards,” *Science of The Total Environment*, 2020.

[72] H. Azadi, D. Petrescu, R. Petrescu-Mag, and A. Ozunu, “Environmental risk mitigation for sustainable land use development,” *Land use policy*, 2020.

[73] Y. Huang, E. Lange, and Y. Ma, “Living with floods and reconnecting to the water–landscape planning and design for delta plains,” *Unable to determine the complete publication venue*, 2022.

[74] V. Cvetkovic and J. Martinović, “Innovative solutions for flood risk management,” *Please check the source or provide more information to complete the publication venue.*, 2020.

[75] N. Kankanamge, T. Yigitcanlar, A. Goonetilleke, *et al.*, “Determining disaster severity through social media analysis: Testing the methodology with south east queensland flood tweets,” *International Journal of Disaster Risk Reduction*, 2020.

[76] L. Zou, D. Liao, N. Lam, M. Meyer, *et al.*, “Social media for emergency rescue: An analysis of rescue requests on twitter during hurricane harvey,” *International Journal of Disaster Risk Reduction*, 2023.

[77] D. Rivera, B. Jenkins, and R. Randolph, “Procedural vulnerability and its effects on equitable post-disaster recovery in low-income communities,” *Journal of the American Planning Association*, 2022.

[78] E. Albright and D. Crow, “Capacity building toward resilience: How communities recover, learn, and change in the aftermath of extreme events,” *Policy Studies Journal*, 2021.

[79] J. Mol, W. Botzen, and J. Blasch, “After the virtual flood: Risk perceptions and flood preparednessafter virtual reality risk communication,” *Judgment and Decision Making*, 2022.

[80] Y. Ge, G. Yang, X. Wang, W. Dou, X. Lu, and J. Mao, “Understanding risk perception from floods: A case study from china,” *Natural hazards*, 2021.

[81] J. Rentschler, M. Salhab, and B. Jafino, “Flood exposure and poverty in 188 countries,” *Nature communications*, 2022.

[82] R. Atanga and V. Tankpa, “Climate change, flood disaster risk and food security nexus in northern ghana,” *Frontiers in Sustainable Food Systems*, 2021.

[83] H. Oskorouchi and A. Sousa-Poza, “Floods, food security, and coping strategies: Evidence from afghanistan,” *Agricultural Economics*, 2021.

[84] A. Echendu, "The impact of flooding on nigeria's sustainable development goals (SDGs)," *Ecosystem Health and Sustainability*, 2020.

[85] M. Hemmati, B. Ellingwood, and H. Mahmoud, "The role of urban growth in resilience of communities under flood risk," *Earth's Future*, 2020.

[86] C. Kousky, H. Kunreuther, M. LaCour-Little, *et al.*, "Flood risk and the US housing market," *Journal of Housing Economics*, 2020.

[87] Y. Parida, "Economic impact of floods in the indian states," *Environment and Development Economics*, 2020.

[88] J. Rentschler and M. Salhab, "People in harm's way," *Flood Exposure and Poverty in*, 2020.

[89] G. Drakonakis, G. Tsagkatakis, *et al.*, "Ombrianet—supervised flood mapping via convolutional neural networks using multitemporal sentinel-1 and sentinel-2 data fusion," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 2022.

[90] A. Sharifi, "Development of a method for flood detection based on sentinel-1 images and classifier algorithms," *Water and Environment Journal*, 2021.

[91] C. Li, J. Dash, M. Asamoah, J. Sheffield, *et al.*, "Increased flooded area and exposure in the white volta river basin in western africa, identified from multi-source remote sensing data," *Scientific Reports*, 2022.

[92] C. Tay, S. Yun, S. Chin, A. Bhardwaj, J. Jung, *et al.*, "Rapid flood and damage mapping using synthetic aperture radar in response to typhoon hagibis, japan," *Scientific data*, 2020.

[93] P. Pandey, P. Chauhan, C. Bhatt, P. Thakur, *et al.*, "… of rockslide triggered flood event in rishiganga and dhauliganga river valleys, chamoli, uttarakhand, india using satellite remote sensing and in situ observations," *Journal of the Indian Society of Remote Sensing*, 2021.

[94] S. Singh, P. Dhote, P. Thakur, A. Chouksey, *et al.*, "Identification of flash-floods-prone river reaches in beas river basin using GIS-based multi-criteria technique: Validation using field and satellite observations," *Natural Hazards*, 2021.

[95] E. Karamuz, R. Romanowicz, *et al.*, "The use of unmanned aerial vehicles in flood hazard assessment," *Journal of Flood Risk Management*, 2020.

[96] O. Pala, I. D. Cetinkaya, *et al.*, "Urban flood exposure and vulnerability: Insights from pendik district of istanbul," *Journal of Flood Risk Management*, 2025.

[97] X. Yan, B. Zhang, Y. Yao, J. Yin, H. Wang, and Q. Ran, "Jointly using the GLDAS 2.2 model and GRACE to study the severe yangtze flooding of 2020," *Journal of Hydrology*, 2022.

[98] G. Mateo-Garcia, J. Veitch-Michaelis, L. Smith, *et al.*, "Towards global flood mapping onboard low cost satellites with machine learning," *Scientific reports*, 2021.

[99] A. Lovari and S. Bowen, "Social media in disaster communication: A case study of strategies, barriers, and ethical implications," *Journal of Public Affairs*, 2020.

[100] C. Fan, F. Wu, and A. Mostafavi, "A hybrid machine learning pipeline for automated mapping of events and locations from social media in disasters," *IEEE Access*, 2020.

[101] Y. Chen, Q. Wang, and W. Ji, "Rapid assessment of disaster impacts on highways using social media," *Journal of Management in Engineering*, 2020.

[102] M. Tsai, C. Yang, J. Chen, and S. Kang, "Four-stage framework for implementing a chatbot system in disaster emergency operation data management: A flood disaster management case study," *KSCE Journal of Civil Engineering*, 2021.

[103] D. Ford and C. Wolf, "Smart cities with digital twin systems for disaster management," *Journal of management in engineering*, 2020.

[104] C. Fan, C. Zhang, A. Yahja, and A. Mostafavi, "Disaster city digital twin: A vision for integrating artificial and human intelligence for disaster management," *International Journal of Information Management*, 2021.

[105] S. Garg, "Next-gen smart city operations with AIOps & IoT: A comprehensive look at optimizing urban infrastructure," *Available at SSRN 5271046*, 2021.

[106] H. Xu, M. Windsor, M. Muste, and I. Demir, "A web-based decision support system for collaborative mitigation of multiple water-related hazards using serious gaming," *Journal of environmental management*, 2020.

[107] H. Nakanishi, S. Wise, Y. Suenaga, and E. Manley, "Simulating emergencies with transport outcomes sim (SETOSim): Application of an agent-based decision support tool to community evacuation planning," *International Journal Of Disaster Risk Reduction*, 2020.

[108] M. Khan, S. Imtiaz, G. Parvaiz, A. Hussain, and J. Bae, "Integration of internet-of-things with blockchain technology to enhance humanitarian logistics performance," *Ieee Access*, 2021.

[109] A. Mukhopadhyay, G. Pettet, M. Kochenderfer, *et al.*, "Designing emergency response pipelines: Lessons and challenges," arXiv preprint arXiv:2010.07504, 2020.