Habitable Planet, 2026, 2(2), 285–302

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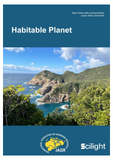

Article

Flood Mapping and Modeling: Progress, Challenges and Future Directions

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ABSTRACT

Floods are among the most widespread and destructive natural hazards, posing persistent threats to human life, infrastructure, and socioeconomic systems worldwide. Over recent decades, flood mapping and modeling have evolved significantly due to advances in remote sensing, Geographic Information Systems (GIS), and data-intensive analytical methods. This review synthesizes recent progress and remaining challenges in flood susceptibility, inundation, hazard, and risk assessment, with particular emphasis on the growing role of machine learning, deep learning, and hybrid modeling frameworks for spatial prediction and decision support. Based on a comprehensive review of more than 130 peer-reviewed studies, the paper examines methodological developments spanning conventional hydrological and hydraulic models, data-driven approaches, and integrated hybrid frameworks. These methods increasingly leverage multi-source geospatial data, including satellite imagery, digital elevation models, rainfall products, and socio-environmental indicators. Emerging research trends reveal a shift toward intelligent data fusion, ensemble modelling, hybrid architectures, and Generative Pre-trained Transformer (GPT) architectures that combine physical process understanding with learning-based algorithms to enhance predictive accuracy, robustness, and scalability across diverse climatic and urban settings. The review also highlights thematic advances in urban flood analysis, flash flood susceptibility mapping, real-time forecasting, and model performance evaluation under data uncertainty. Despite substantial progress, key challenges persist related to model generalization, interpretability, data quality, and operational implementation. By critically assessing current methodologies and research gaps, this study outlines future directions for next-generation Geospatial Artificial Intelligence (GeoAI) in flood mapping and modeling.

ARTICLE INFO

History:

Received: 10 February 2026
Revised: 17 March 2026
Accepted: 12 April 2026
Published: 20 April 2026

Keywords:

flood mapping;
flood modeling;
Geospatial Artificial Intelligence (GeoAI);
machine learning;
disaster risk assessment

Citation:

Isazadeh, V.; Shirmohammadi, M.; Pirasteh, S.; et al. Flood Mapping and Modeling: Progress, Challenges and Future Directions. *Habitable Planet* **2026**, *2*(2), 285–302. https://doi.org/10.63335/j.hp.2026.0039

Research Highlights

- Reviews 130+ studies on AI-driven flood mapping and modeling advances.
- Highlights hybrid, ensemble, and data-fusion methods for improved flood prediction.
- Identifies key gaps and future directions for next-generation GeoAI in flood analysis.

1. Introduction

Hydrological modeling and flood mapping together provide the scientific and spatial foundation for understanding flood processes, assessing risks, and supporting effective flood management. Hydrological models describe water movement, runoff generation, and flow dynamics across catchments, while flood mapping translates these processes into spatial representations of inundation extent, depth, and potential impacts. The integration of these two components has become increasingly important for improving flood prediction, risk assessment, and decision-making in both urban and rural environments. Flooding remains a major environmental challenge worldwide, with significant consequences for infrastructure, ecosystems, and human communities [1–6]. Reliable flood mapping therefore, plays a critical role in identifying hazard-prone areas, evaluating exposure and vulnerability, and guiding mitigation and adaptation strategies [7, 8]. Traditional hydrological and hydraulic models have provided valuable insights into flood processes for several decades. However, these approaches often face limitations related to computational efficiency, data availability, and scalability when applied to large or rapidly changing environments. As climate change, rapid urbanization, and environmental degradation continue to alter hydrological regimes, there is a growing need for more adaptive, data-driven flood-mapping frameworks.

Urbanization represents a particularly significant driver of flood risk. By 2050, nearly two-thirds of the global population is expected to live in urban areas, placing increasing pressure on infrastructure, land-use systems, and water management networks (available at https://unhabitat.org/annual-report-2023 (accessed on 10 January 2024)). Urban landscapes often contain dense populations, complex land-use patterns, and highly modified drainage systems that alter natural hydrological responses. In many regions, urban expansion has occurred without adequate consideration of flood hazards, increasing vulnerability and complicating disaster preparedness efforts [5, 6, 9]. Historical settlement patterns also demonstrate that both urban and rural communities are frequently located in flood-prone areas, reinforcing long-term exposure to hydrological hazards [10–12].

In response to these challenges, recent advances in remote sensing, Geographic Information Systems (GIS), and Artificial Intelligence (AI) have significantly expanded the capabilities of flood mapping and hydrological modeling. Machine learning and deep learning algorithms, including Random Forests (RF), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Pre-trained Transformer (GPT) architectures, are increasingly applied to analyze large and heterogeneous datasets such as satellite imagery, digital elevation models (DEMs), rainfall observations, and hydrological variables [5, 13, 14]. Cloud-based geospatial platforms such as Google Earth Engine (GEE) have further accelerated these developments by enabling near-real-time processing of multi-sensor satellite data, including Sentinel-1, Sentinel-2, and Landsat imagery [15–20]. These technological advances have contributed to the emergence of Geospatial Artificial Intelligence (GeoAI), which integrates geospatial technologies with advanced AI methods to support automated spatial analysis and predictive modeling. GeoAI enables tasks such as semantic segmentation, object-based flood detection, and multi-source data fusion across meteorological, hydrological, and socioeconomic datasets [21–27]. Such capabilities enhance flood-susceptibility analysis and enable more sophisticated modelling frameworks that can operate across diverse climatic and geographic conditions.

Despite these advancements, several challenges continue to limit the operational implementation of AI-driven flood mapping systems. In many regions, geospatial datasets remain incomplete or unevenly distributed. For example, as of March 26, 2025, OpenStreetMap (OSM) contained approximately 616 million building footprints, representing only about 15% of global structures, indicating significant gaps in geospatial information needed for disaster preparedness and sustainable development [28–31]. In addition, issues related to model generalization, interpretability, and integration with operational decision-support systems remain important research challenges.

Against this background, this study presents a comprehensive review of approximately 130 scholarly articles that examine the evolution of flood mapping and hydrological modeling across traditional approaches, remote sensing and GIS-based techniques, machine learning, deep learning, and emerging AI-driven frameworks [32–34]. The review analyzes key research themes using selected keywords, including flood mapping, hydrological modelling, machine learning, deep learning, AI, susceptibility, hazard, and risk. These keywords were used to generate a systematic review map highlighting the field's major research hotspots (Figure 1).

To ensure transparency and reproducibility, the literature included in this review was identified through a structured search of major scientific databases, including Web of Science, Scopus, and Google Scholar. The search focused on peer-reviewed journal articles in hydrology, geospatial analysis, remote sensing, and artificial intelligence. A combination of keywords was used to capture relevant studies, including flood mapping, hydrological modeling, flood susceptibility, machine learning, deep learning, artificial intelligence, GIS, remote sensing, hazard assessment, and flood risk. These keywords were applied individually and in combination to identify studies addressing the evolution of flood mapping and modeling techniques. The initial search results were subsequently screened to remove duplicate records and studies not directly related to flood analysis. The inclusion criteria prioritized peer-reviewed publications that (i) addressed flood susceptibility, inundation mapping, or hydrological modeling, (ii) applied geospatial, remote sensing, or AI-based methodologies, and (iii) provided methodological or analytical contributions relevant to flood risk assessment. Studies focusing solely on unrelated environmental hazards or lacking methodological detail were excluded. Following this screening process, approximately 130 studies were selected for detailed analysis and synthesis within this review. The selected publications were further analyzed to identify methodological trends, commonly used modeling techniques, and emerging research directions. Keywords extracted from these studies were used to generate bibliometric visualizations of research hotspots and methodological networks in VOSviewer, which support the systematic review maps presented in Figures 1 and 2.

The objective of this review is to synthesize current knowledge, identify methodological trends, and highlight key research gaps in flood mapping and modeling. By evaluating recent technological developments and emerging analytical frameworks, the study aims to provide insights that support the development of more adaptive, scalable, and intelligent geospatial solutions for flood risk management. The following section, therefore, examines recent research trends, methodological advances, and existing challenges in AI-driven flood mapping and hydrological modeling, providing the conceptual foundation for the analyses presented in this review (Figure 2).

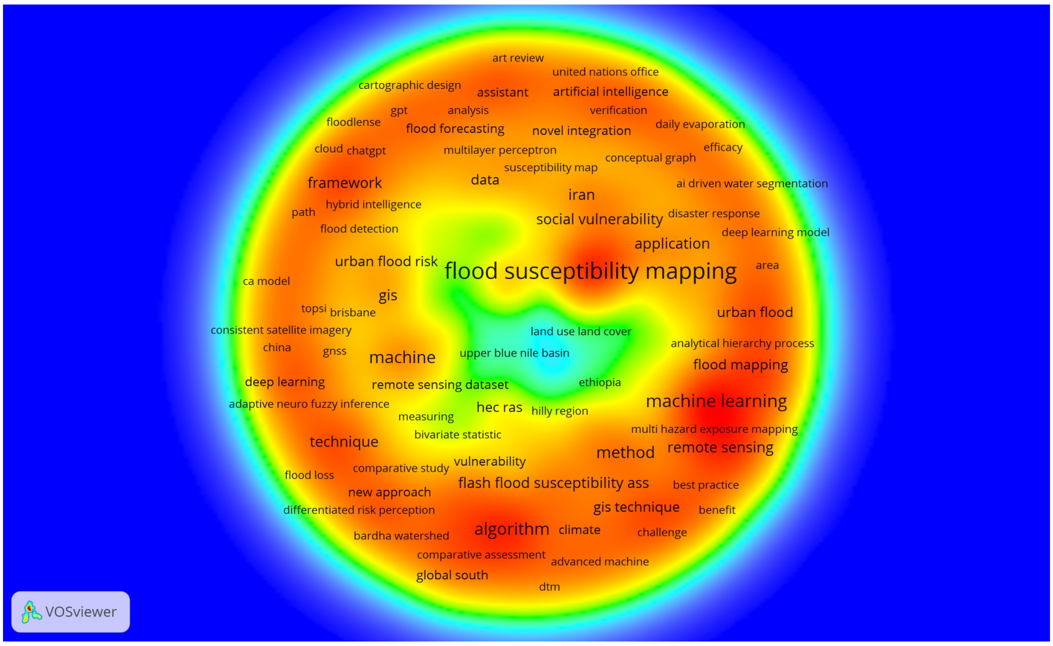


Figure 1. Hotspots of the systematic review of indexed keywords network (generated by VOSviewer).

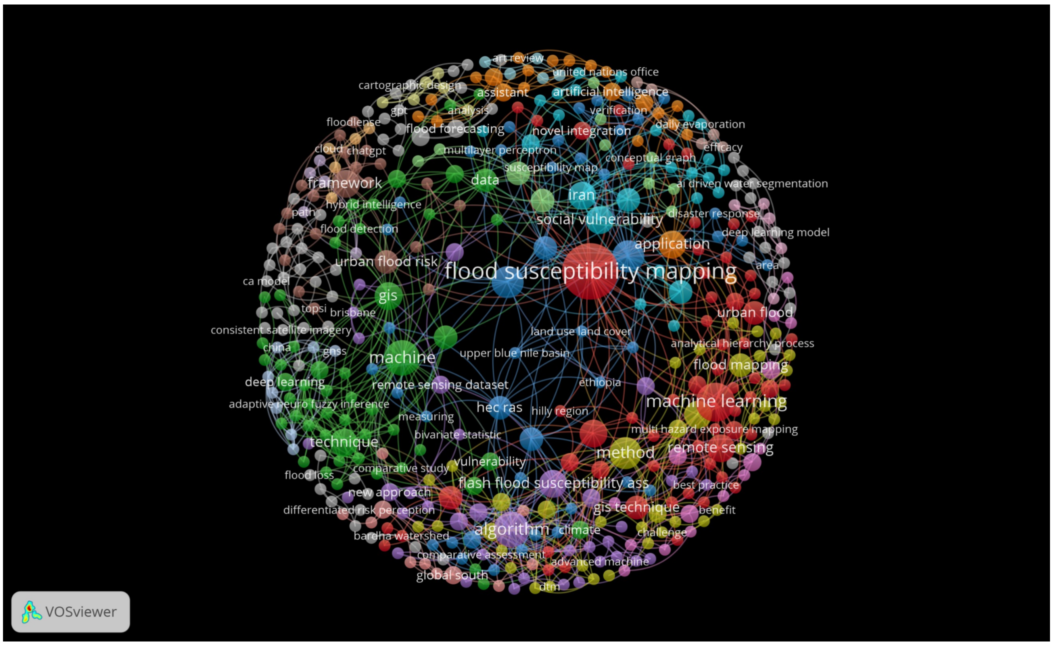


Figure 2. Networks of the systematic review of indexed keywords network (generated by VOSviewer).

To improve the organization and clarity of this review, the literature on flood mapping and hydrological modeling can be conceptually structured into four main domains, each addressing different aspects of flood processes and analysis. First, flood susceptibility mapping (FSM) identifies areas prone to flooding based on environmental, topographic, and hydrological conditioning factors, typically using statistical, machine-learning, or hybrid approaches. Second, flood inundation modeling aims to simulate the spatial extent, depth, and duration of floodwaters under specific scenarios, often integrating hydrological inputs with terrain data. Third, hydrodynamic simulation involves physically based modeling of water flow dynamics using numerical methods (e.g., one-dimensional or two-dimensional hydraulic models) to represent flow velocity, discharge, and interactions with channel and floodplain systems. Fourth, remote sensing–based flood detection uses satellite and aerial imagery (e.g., SAR and multispectral data) to map observed flood extents, support model calibration, and enable near-real-time monitoring.

While these domains are conceptually distinct, they are highly interconnected. For example, remote sensing data are frequently used to validate inundation models, while hydrodynamic simulations provide physically consistent inputs for susceptibility assessments. Similarly, machine learning and GeoAI approaches are increasingly applied across all domains to enhance predictive performance and automate analysis. This conceptual framework provides a structured basis for reviewing and comparing existing studies and helps to position different methodologies within the broader context of flood risk assessment.

2. Related Work

This review addresses three primary objectives. First, it investigates current research trends in the use of AI, machine learning, deep learning, and advanced algorithms within hydrological modelling and flood mapping. Second, it evaluates how recent studies have implemented data-driven and hybrid modelling strategies to improve flood susceptibility assessment, inundation mapping, and predictive performance. Third, it identifies research gaps and methodological limitations in existing approaches to highlight future research needs and support the development of more robust, scalable, and transferable AI-driven flood modelling frameworks.

To accomplish these objectives, a comprehensive literature survey was conducted focusing on hydrological modelling, flood susceptibility mapping, and AI-based geospatial analysis. The reviewed studies encompass a wide spectrum of methodological approaches, including traditional hydrological and hydraulic models, machine learning algorithms, deep learning architectures, and hybrid frameworks that combine physical process knowledge with data-driven techniques. Through this synthesis, the review provides a structured perspective that facilitates benchmarking and methodological comparison across flood-mapping studies.

We perform bibliometric analysis to identify emerging research trends, thematic clusters, and dominant methodological directions within the literature. Keyword co-occurrence analysis was carried out using VOSviewer (https://www.vosviewer.com), which enabled visualization of research hotspots and the evolution of key topics in flood mapping and modelling. Detailed methodological explanations regarding hotspot map generation and network analysis can be found in Piadeh et al. [35] and Aziz et al. [36].

Representative studies identified through the review are summarized in Table 1. In contrast, Table 2 provides additional methodological insights from selected literature reviews and conceptual studies related to AI, GeoAI, and emerging Large Language Models (LLM) applications. The temporal evolution of publications included in the review is illustrated in Figure 3, and the prevalence of modelling techniques is shown in Figure 4. Furthermore, Figure 5 presents the network distribution of modelling approaches generated using VOSviewer. Collectively, these analyses reveal the most frequently used techniques and illustrate shifting methodological preferences in flood-mapping and hydrological-modelling research.

The bibliometric analysis based on VOSviewer provides important insights into the thematic evolution and research priorities in flood mapping and hydrological modeling. The keyword co-occurrence network reveals several dominant clusters representing major research domains, including (i) traditional hydrological modeling and flood risk assessment, (ii) GIS and remote sensing-based flood mapping, (iii) machine learning and deep learning applications, and (iv) emerging GeoAI and data-driven frameworks. The spatial distribution of these clusters indicates a clear shift in research focus over time, from physically based and GIS-supported approaches toward more data-intensive and automated methodologies. In particular, earlier studies are strongly associated with keywords such as hydrological modeling, flood risk, watershed analysis, and hydraulic simulation, reflecting a focus on process-based understanding of flood dynamics. More recent clusters highlight the increasing prominence of terms such as machine learning, deep learning, remote sensing, Sentinel data, and flood susceptibility, indicating the rapid adoption of data-driven approaches. The emergence of keywords related to GeoAI, big data, and cloud computing further suggests a transition toward scalable, real-time, and integrative flood mapping systems. These patterns demonstrate not only technological advancement but also a paradigm shift in flood research, where the integration of multi-source geospatial data and intelligent algorithms is becoming central to flood prediction and risk assessment. At the same time, the relatively limited presence of keywords related to interpretability, uncertainty analysis, and operational deployment highlights ongoing research gaps that require further attention.

Table 1. Summary of studies on flood susceptibility and prediction models.

Source	Evaluation Metrics	Models Used	Objective
[37–39]	PPV, Sensitivity, Specificity, Accuracy, RMSE, Kappa, ROC Curve	AdaBoostM, Bagging, Dagging, MultiBoostAB, Credal Decision Tree	Hybrid computational GIS-based approaches for flash flood susceptibility assessment
[40, 41]	False Positive Rate, AUC	SVM, RF, MaxEnt, BRT, MARS, GLM, GAM, Ensemble	Urban flood risk mapping using data-driven spatial methods
[42–45]	AUC, Kappa	GARP, QUEST, FANP	Urban flood risk mapping comparing GARP and QUEST models
[46–48]	AUC, RMSE, MSE	CNN, RNN	Urban flood modeling in Seoul using deep learning approaches
[49–51]	AUC	MLP, Autoencoder-MLP	Flood susceptibility mapping using MLP and autoencoder hybrid models
[41, 52, 53]	TPR, TNR, Specificity, Sensitivity, AUC	Naïve Bayes, Random Forest, BART	Flood susceptibility modeling using the NBART approach
[54, 55]	AUC	CART, FDA, GLM, GAM, BRT, MARS, MaxEnt, Ensemble models	New ensemble forecasting approaches combining machine learning and statistical models
[38, 41]	Specificity, Sensitivity, Accuracy, F1, Jaccard, MCC, RMSE, AUC	DBN, ELM, PSO, LR, ANN, LMT, FTree, ADTree	Comparing deep learning and machine learning models for flood susceptibility
[56]	Sensitivity, Specificity, Accuracy, ROC-AUC, Kappa	HP, SVR, HP-SVR	Flood susceptibility assessment using HP-SVM ensemble algorithms
[57–59]	Accuracy, Kappa, RMSE, AUC, Friedman, Wilcoxon tests	LMT, REPT, NBT, ADT	Comparative evaluation of decision tree algorithms for flash flood modeling
[60, 61]	Sensitivity, Specificity, Accuracy, Kappa, RMSE, MAE, AUROC	Adabag, Rotation Forest, NSC, KNN, Logit Boost, BRT ensembles	Novel ensemble machine learning models for flood susceptibility mapping
[62, 63]	Sensitivity, Specificity, Accuracy, Kappa, TSS, AUC	BRT, GLM	Flood-prone area evaluation using Google Earth Engine
[64, 65]	Sensitivity, Specificity, Accuracy, AUC	AHP, KNN, Lazy K-Star	Flash flood susceptibility using MCDA and ML techniques
[66]	Sensitivity, Specificity, PPV, NPV, AUC	BRT, RF, PRF, RRF, ERT	Flash flood modeling using ensemble tree-based ML algorithms
[67]	Sensitivity, Specificity, AUC	ANN, DL, PSO-optimized	Deep learning with PSO optimization for flood hazard mapping in Brisbane, Australia
[68, 69]	TPR, AUC, Efficiency, TSS, MCC, Sensitivity, Specificity	ML, PNN, BRT, RF, Hybrid Multi-Boost	Developing hybrid multi-boost MLP neural network for urban flood prediction
[70, 71]	Sensitivity, Specificity, Accuracy, MCC, F-score, MR, RMSE	SVR, Wavelet Kernel, Bat Algorithm (BA), GWO	New hybrid models for urban flood susceptibility mapping
[72]	Sensitivity, Specificity, TP, FN, TN, FP, AUC	RF, SVM, BRT	Urban flood risk assessment using hybrid TOPSIS and ML methods
[47, 48, 58]	RMSE, MSE, AUC	Convolutional Neural Network (CNN)	Nationwide flood hazard prediction using CNN in Iran
[69, 73]	Specificity, PPV, NPV, AUC	BT, ANN, DLNN, DLT, Deep Boosting	Evaluating hybrid deep learning algorithms combining trees and neural networks

Table 2. Selected examples of literature review- AI, GeoAI, LLMs, and flood mapping.

Reference	Study Description/Focus	Methods/Approach	Pros	Cons/Limitations
[30, 74]	Global assessment of flood frequency and impacts	Statistical analysis, historical flood records	Highlighted global flood risk trends; quantified human & economic impacts	Did not explore predictive modeling or AI applications
[30, 75, 76]	Global disaster statistics, flood fatalities	Historical dataset analysis	Provided comprehensive baseline data	Lacks modeling or predictive capability
[51, 77]	Flood Susceptibility Mapping (FSM) using WoE and Fuzzy Logic	Weights of Evidence, Fuzzy logic models	Interpretable; expert-driven; simple	Limited in capturing nonlinear and dynamic flood processes
[78, 79]	Multi-Criteria Decision Analysis (MCDA) for flood zones	AHP, ANP, logistic regression	Integrates expert knowledge; interpretable	Static; limited dynamic/temporal modeling
[48, 66, 80–82]	Flash Flood Susceptibility using physically-based hydrological models	Rainfall-runoff simulation using geomorphology	Provides physically meaningful outputs	Assumes linearity; limited spatial/temporal resolution
[57, 83]	Hydrological models for flood prediction	HEC-RAS, 1D hydraulic models	Well-established; reliable for specific cases	Limited incorporation of spatiotemporal variability
[1–3, 69, 81, 82]	ANN/ML/DL for FSM	ANN/Random Forest, XGBoost, SVM, CNN-LSTM	High predictive accuracy; can integrate multi-source data	Requires large datasets; computationally intensive
[4, 84–86]	ML + satellite imagery for flood mapping	GRACE, Sentinel-1, Sentinel-2, Landsat; RF, XGBoost	Improved Automation and real-time mapping	May be sensitive to missing or low-resolution data
[25, 87]	Hybrid CNN-LSTM-Attention for FSM with CMIP6 climate projections	Deep learning and climate model integration	Captures spatiotemporal patterns; climate-informed; scalable	Complexity; computational cost; requires high-quality historical inventories
[88, 89]	Flood extent segmentation using U-Net + SAR	Sentinel-1 imagery and CNN	High spatial resolution; generalizable	Requires pre-processing; model performance varies by terrain
[90]	AI-driven water segmentation (U-Net, ResNet, DeepLabv3)	Drone imagery, field data	Strong pixel-wise accuracy; flexible input sources	Trade-offs between complexity and robustness; may overfit
[91]	SATGPT: LLM for flood map generation	GPT to generate GEE code	Reduces technical barrier; rapid mapping	Lacks direct physical validation; numeric precision may be limited
[92]	GPT-assisted hydrological risk mapping	GPT-4 as scripting assistant	Speeds up GIS workflows; automates repetitive tasks	Not fully autonomous; relies on correct prompt input
[93]	Physics-informed GANs for future flood scenario imagery	Generative models and physics	Engaging visuals; risk communication	Proof-of-concept; may lack fine-scale accuracy
[94]	Review of deep learning for flood mapping	U-Net, CNN, segmentation networks	Comprehensive survey; identifies best practices	Limited discussion on LLM integration
[95–98]	GeoAI and LLM integration in GIS/cartography	LLM and geospatial workflows	Improves accessibility and efficiency; supports complex queries	Few applications for actual flood mapping; physical grounding not always ensured

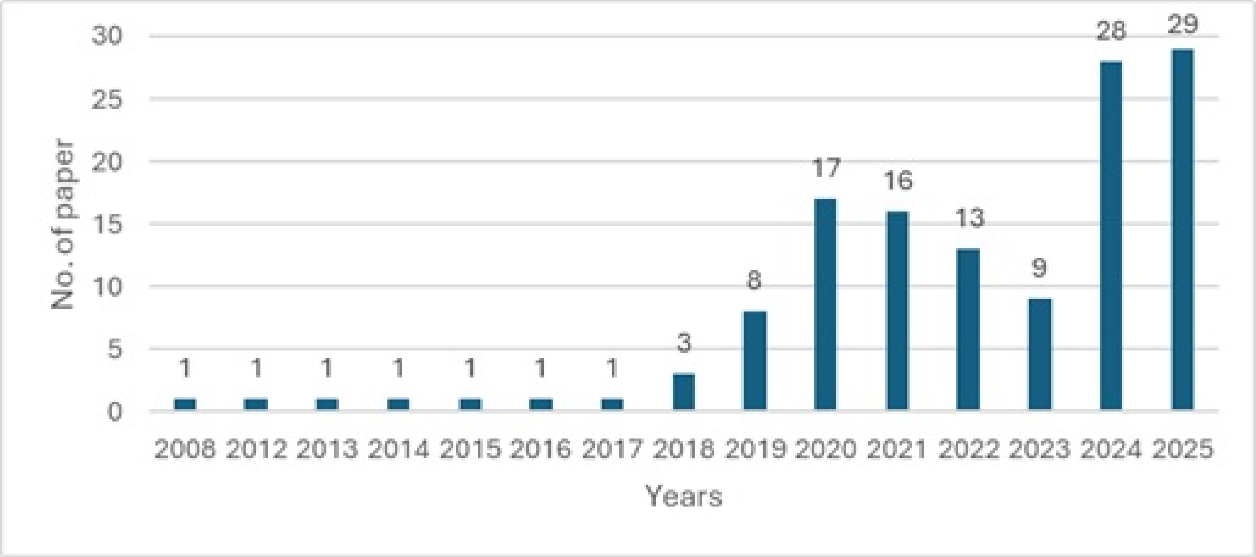


Figure 3. Number of publications vs. year.

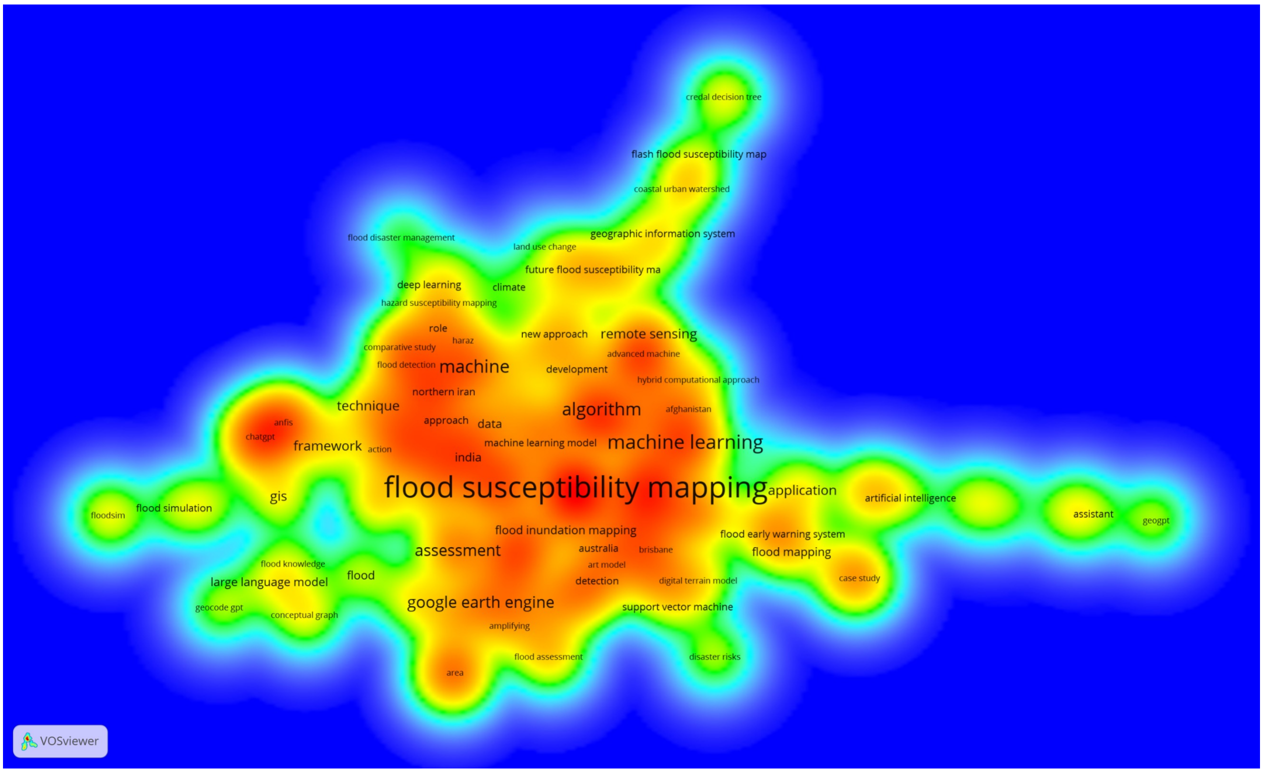


Figure 4. Hotspots' distribution of methods used (generated by VOSviewer).

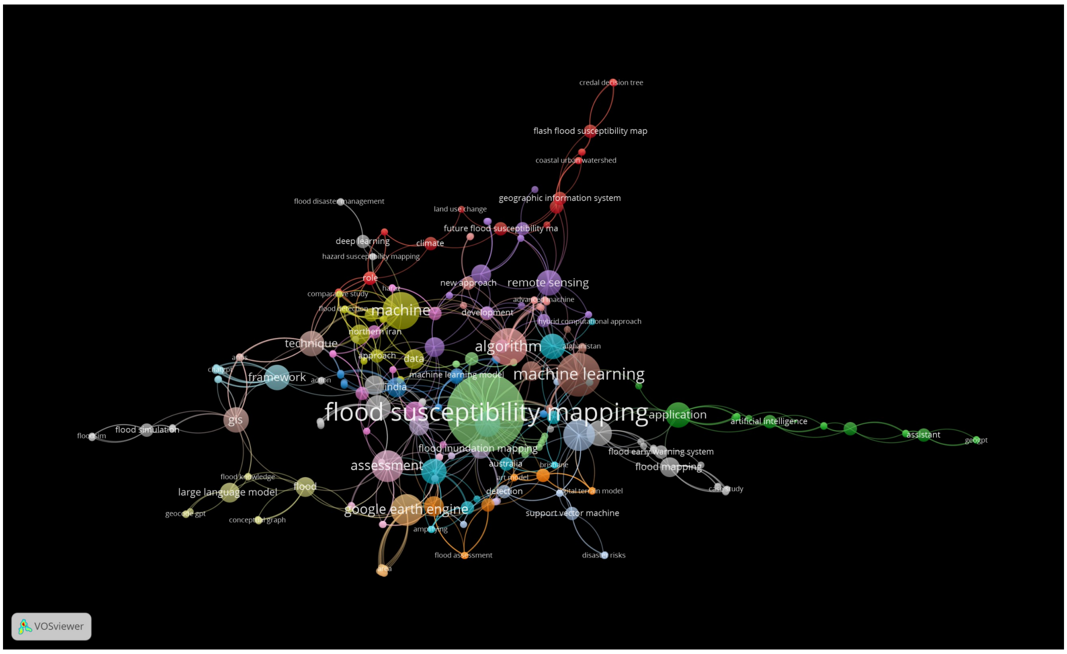


Figure 5. Networks' distribution of methods used (generated by VOSviewer).

2.1. AI and Machine Learning Trends in Flood Mapping and Hydrological Modeling

Floods are among the most frequent and destructive natural hazards worldwide, threatening human life, infrastructure, ecosystems, and economic stability. Over the past several decades, both the frequency and intensity of flood events have increased, largely driven by climate change, rapid urbanization, deforestation, and widespread land use transformations [74, 99]. According to the United Nations Disaster Risk Reduction (UNDRR), floods account for approximately 43% of global disaster events [75, 76]. Between 2000 and 2025 alone, more than 218,000 fatalities were recorded across over 4700 flood disasters affecting 168 countries. Although improvements in early warning systems and disaster preparedness have reduced average annual fatalities to fewer than 10,000 [99–102], catastrophic events such as the 2006 floods in North Korea, the 2020 South Asia floods, and the 2023 Derna flood in Libya demonstrate that flood hazards remain a persistent and evolving global challenge [103, 104]. These risks are expected to intensify further in regions characterized by complex terrain and limited infrastructure, such as Golestan Province in northeastern Iran [25, 74, 87].

Within this context, Flood Susceptibility Mapping (FSM) has become an essential component of disaster risk reduction, spatial planning, and long-term resilience building. By identifying areas prone to flooding, FSM supports proactive, evidence-based decision-making in urban planning, infrastructure design, and emergency management. Historically, flood mapping relied on physically based hydrological processes supported by field surveys, topographic maps, aerial photography, remote sensing imagery, and historical flood records. Field-based investigations documented flood marks, inundation boundaries, and water-depth observations after flood events, which were then integrated with terrain data to delineate flood-prone zones [35, 36]. Hydrological and hydraulic models such as rainfall-runoff simulations and HEC-RAS were subsequently applied to estimate discharge, flow dynamics, and inundation extents using geomorphological and hydrological parameters [105–112]. Kaya & Derin [113] reported considerable variability in the selection of conditioning parameters in FSM studies, with the number of variables typically ranging from 5 to 21.

The major strength of these conventional approaches lies in their strong physical interpretability and grounding in hydrological theory. They provide meaningful insight into flood processes and remain essential for local-scale studies where detailed observations are available. However, several limitations have been widely recognized. These approaches are often labour-intensive and time-consuming, and are frequently constrained to regions with reliable long-term observations. Their predictive performance is highly dependent on data quality, while simplified one-dimensional formulations may struggle to capture spatial heterogeneity and rapid hydrological responses, limiting their applicability for real-time monitoring and flash-flood analysis [57, 114]. Additionally, missing observations, sparse historical records, and survival bias introduce systematic uncertainties that can reduce model reliability [115, 116].

The emergence of machine learning (ML) and deep learning (DL) has significantly transformed flood susceptibility and hazard mapping. Classical Artificial Neural Networks (ANNs) and widely used machine learning algorithms such as RF, Support Vector Machines (SVM), XGBoost, and AdaBoost have demonstrated strong predictive capabilities when integrated with satellite imagery from platforms such as Sentinel-1, Sentinel-2, and Landsat, as well as environmental conditioning variables [1, 78, 81, 82, 84, 117–119]. Comparative analyses, including the work of Wahba et al. [43], show that ANN-based Multilayer Perceptron (MLP) and Support Vector Regression (SVR) models can achieve high prediction accuracy, though their performance varies across geographic contexts.

Recent developments in deep learning have further enhanced the ability to capture complex spatial and temporal relationships in hydrological systems. Architectures such as CNNs, Long Short-Term Memory (LSTM) networks, and hybrid CNN-LSTM models enable automated feature extraction from large geospatial datasets and facilitate explicit modelling of spatiotemporal flood dynamics [25, 87, 120]. ConvLSTM-based flood forecasting models have shown improved performance compared with traditional methods by simultaneously capturing spatial patterns and temporal dependencies in hydrological processes [121]. Similarly, integrating CNNs, RNNs, and Neural Ordinary Differential Equations has improved flash-flood runoff prediction by representing continuous-time hydrological dynamics [48]. The advantages of ML and DL methods include high predictive accuracy, scalability, automation, and the ability to integrate large and heterogeneous datasets. Optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Quantum Particle Swarm Optimization (QPSO) have further enhanced parameter calibration and sensitivity analysis in flood-mapping models [80–82, 122]. Additionally, ensemble learning techniques and semi-supervised approaches improve model robustness in data-scarce environments [2, 3, 123–125]. Despite these advances, significant challenges remain. Many machine learning and deep learning models lack interpretability, require extensive training data, and often struggle to generalize across diverse climatic and geographical contexts.

2.2. Data-driven and Hybrid Approaches for Flood Susceptibility and Prediction

In response to the limitations of purely physical or purely data-driven approaches, recent research increasingly focuses on hybrid modelling frameworks that combine hydrological knowledge with machine learning and geospatial data analytics. These approaches aim to leverage the strengths of both methodologies: the interpretability of physically based models and the predictive power of data-driven algorithms.

Recent studies have incorporated climate projections and land-use change models into flood susceptibility frameworks to evaluate future flood scenarios under changing environmental conditions. For example, models integrating CMIP6 climate projections, Cellular Automata-Markov (CA-MARKOV) simulations, Shared Socioeconomic Pathways (SSPs), and Representative Concentration Pathways (RCPs) have been applied to assess long-term flood risk under climate change scenarios [25, 87, 126, 127]. Such integrated approaches allow researchers to evaluate how future climate variability and urban expansion may influence flood hazards. Moreover, hybrid models that combine neuro-fuzzy systems, optimization algorithms, and ensemble learning techniques have demonstrated promising improvements in predictive performance. Feature-selection algorithms and ensemble frameworks help identify the most influential conditioning variables, thereby improving the stability and reliability of flood-susceptibility predictions [64, 106, 128]. These approaches provide important advantages for scenario-based risk assessment and policy-oriented planning, particularly in regions experiencing rapid environmental change.

Additionally, advances in GeoAI-driven flood mapping represent another important development in this field. Deep learning segmentation networks such as U-Net, ResNet, and DeepLabv3 have been applied to Synthetic Aperture Radar (SAR), multispectral imagery, and Unmanned Aerial Vehicle (UAV) data to detect flood extents and evaluate susceptibility patterns with high spatial resolution [88, 90–92, 94]. Integrating Sentinel-1 SAR imagery with Moderate Resolution Imaging Spectroradiometer (MODIS) time-series data using CNN-LSTM architectures within cloud platforms such as GEE enables long-term reconstruction of inundation events and improves performance compared with threshold-based or purely physical models. Table 1 summarizes representative studies employing machine learning, deep learning, and hybrid frameworks for flood susceptibility and prediction. These studies demonstrate the diversity of modelling approaches and evaluation metrics used in the literature.

While Tables 1 and 2 provide a structured overview of the reviewed studies, a critical comparison of modeling approaches reveals significant differences in performance, applicability, and limitations across flood-susceptibility and hydrological modelling tasks. Machine learning models such as RF and SVM are widely recognized for their robustness and ability to handle nonlinear relationships and high-dimensional datasets. RF, in particular, demonstrates strong performance in variable importance analysis and resistance to overfitting; however, it may struggle with spatial dependency representation. SVM models are effective in high-dimensional spaces but are sensitive to parameter selection and kernel design, which can limit their transferability across regions. Deep learning approaches, including ANNs and CNNs, have demonstrated superior ability to capture complex spatial patterns and feature hierarchies, especially when applied to remote sensing data. CNN-based models are particularly effective for flood extent mapping and image-based classification tasks due to their spatial feature extraction capabilities. However, these models typically require large training datasets and significant computational resources, and their “black-box” nature limits interpretability in decision-making contexts.

Moreover, hybrid and ensemble approaches have emerged as a promising direction to overcome the limitations of individual models by combining complementary strengths. For example, integrating machine learning algorithms with optimization techniques or physically based hydrological models can improve prediction accuracy and generalization performance. Nevertheless, these approaches often increase model complexity and computational cost, posing challenges for real-time and large-scale applications. Overall, no single modeling approach consistently outperforms others across all scenarios. Data availability, spatial scale, computational resources, and the specific objectives of the study should therefore guide model selection. This highlights the need for more standardized benchmarking frameworks and comparative studies to support the development of robust, transferable flood-mapping models [90–94]. It is worth noting that the increasing use of satellite imagery, high-resolution terrain data, and geospatial big data has significantly improved the automation and scalability of flood-mapping workflows. Nevertheless, challenges remain, including incomplete geospatial datasets, insufficient infrastructure coverage, limited uncertainty quantification, and difficulties in transferring models across regions.

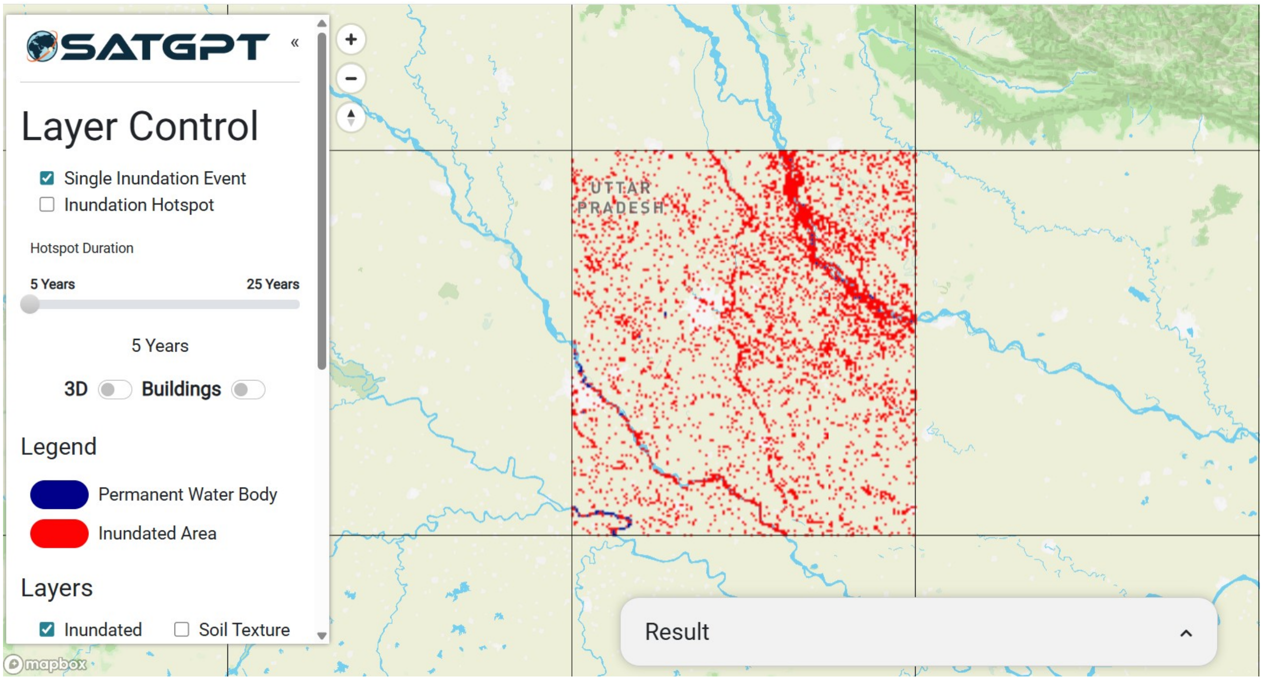
2.3. Research Gaps and Emerging Challenges in AI-driven Flood Mapping

Despite significant methodological progress, several important research gaps persist in AI-driven flood mapping. While machine learning and deep learning approaches have substantially improved predictive accuracy and automation, the integration of spatial, temporal, climatic, and socioeconomic dimensions remains limited. Many existing models are developed for specific geographic regions and may not generalize well to other hydrological or climatic contexts. Interpretability represents another critical challenge. Complex machine learning models often operate as “black boxes,” making it difficult for researchers and decision-makers to understand the mechanisms that drive their predictions. Improving model transparency and incorporating explainable AI techniques will therefore be essential for operational flood-risk management.

Another emerging research frontier involves the integration of LLMs and GPT architectures into geospatial workflows. For example, Mehmood [91] explored the potential of GPT-based systems to identify flooded regions and generate geospatial analysis workflows (Figure 6). Such systems may significantly reduce technical barriers to GIS analysis by enabling natural-language interaction with geospatial data and automating complex analytical tasks. However, these approaches remain at an early stage of development. Current GPT-based systems often lack direct physical validation and may struggle with precise numerical calculations or spatial reasoning. Consequently, further research is needed to integrate LLM-based interfaces with physically grounded hydrological models and reliable geospatial datasets.

Although GeoAI, GPT, and other LLM-based approaches have recently attracted attention in geospatial analysis, their application in flood mapping and hydrological modelling remains at an early, largely experimental stage. Unlike established data-driven and physically based models, such as CNNs, RNNs, and hydrodynamic simulations, LLM-based systems have not yet been widely validated through empirical studies or operational deployments in flood risk assessment. The SATGPT [91] example presented in this study should therefore be interpreted as a conceptual demonstration of how LLMs can assist in geospatial query processing, workflow generation, and knowledge extraction, rather than as a validated flood-mapping model. Current limitations of LLM-based approaches include the lack of direct integration with physically based hydrological processes, limited capability for precise spatial reasoning and numerical simulation, and insufficient validation using ground truth flood data. As a result, their role is better framed as complementary tools that can enhance user interaction, automate analytical workflows, and support decision-making, rather than replacing established modelling frameworks. Future research should focus on integrating LLMs [95–98] with remote sensing data, GIS platforms, and hydrodynamic models, as well as developing validation protocols to assess their reliability and applicability in real-world flood scenarios.

Despite significant advancements in flood mapping and hydrological modeling, several critical challenges continue to limit the reliability and operational applicability of existing approaches. One of the primary concerns is model uncertainty, which arises from multiple sources, including input data quality, model structure, parameter selection, and scale mismatches. For example, uncertainties in rainfall measurements, digital elevation models (DEMs), and land-use data can propagate through both physically based and machine learning models, leading to variations in predicted flood extent and susceptibility. Transferability of models across regions remains another major challenge. Many machine learning and deep learning models are trained on region-specific datasets and may not generalize well when applied to areas with different climatic conditions, topography, or hydrological characteristics. This limitation reduces model scalability and necessitates region-specific calibration, which can be time-consuming and data-intensive. Data limitations further constrain model development, particularly in data-scarce regions where high-resolution and multi-temporal datasets are unavailable or incomplete. Inconsistent data quality, missing observations, and limited ground truth information hinder model validation and reduce confidence in predictive outputs. Additionally, regional variability in environmental conditions, such as differences in watershed characteristics, soil properties, and urban infrastructure, introduces further complexity, making it difficult to develop universally applicable models. These challenges highlight the need for future research to focus on improving uncertainty quantification, developing transferable and generalizable models, and integrating multi-source geospatial data through hybrid and ensemble approaches. Advancing explainable AI techniques, establishing standardized evaluation frameworks, and incorporating region-specific knowledge into model design will be essential for enhancing the robustness and operational readiness of flood mapping systems.



☑ Single Inundation Event
☐ Inundation Hotspot

Hotspot Duration
5 Years 25 Years
5 Years

3D ○ Buildings ○

Legend
🟦 Permanent Water Body
🟥 Inundated Area

Layers
☑ Inundated ☐ Soil Texture

Figure 6. SATGPT: prompt "*How big was the flood in North India in 2020?*"

Moreover, GPT architectures have attracted considerable attention in natural language processing and geospatial data analysis; their application in FSM and hydrological modelling remains relatively limited compared with established deep learning approaches, such as CNNs and RNNs [82, 83]. Nevertheless, GPT-based systems offer promising opportunities for future FSM frameworks. By integrating large language models with geospatial databases, satellite imagery platforms, and hydrological datasets, GPT models could assist in automated feature extraction, interpretation of spatial relationships, and generation of analytical workflows for flood risk assessment. For example, GPT-driven systems may support automated generation of GIS or GEE [91] scripts, integration of heterogeneous environmental datasets, and the development of interactive decision-support tools for flood risk management. In future research, hybrid frameworks combining GPT-based reasoning with physically based hydrological models and machine learning algorithms may enhance model interpretability, facilitate knowledge-driven flood analysis, and improve accessibility for non-expert users.

3. Discussion

3.1. Challenges and Opportunities

The integration of next-generation geospatial intelligence, particularly through GeoAI and advanced AI-driven analytical frameworks, has the potential to fundamentally transform hydrological modeling, flood mapping, and disaster management [2, 3, 106, 123–125]. These technologies offer new opportunities to improve predictive accuracy, enhance decision-making, and broaden access to complex geospatial analyses across scientific, institutional, and operational domains. However, a synthesis of more than 130 reviewed studies indicates that adopting AI in flood-related applications is accompanied by significant technical, operational, and governance challenges. Addressing these challenges is essential for guiding future research, technological development, and real-world implementation.

The identified challenges can be grouped into several interrelated categories. First, data quality and availability remain critical constraints [115, 116]. Flood mapping relies heavily on accurate, high-resolution spatial datasets, including satellite imagery, digital elevation models, and hydrological observations. Despite progress in remote sensing and open-access platforms, many regions still suffer from limited spatial coverage, insufficient temporal resolution, and inconsistent data standards. Incomplete or outdated datasets can propagate uncertainty through AI-driven models, undermining the reliability of flood susceptibility and risk assessments. Second, model complexity and interpretability present persistent obstacles. While deep learning and hybrid AI models often achieve high predictive performance, their internal decision-making processes are frequently opaque. This lack of transparency limits stakeholder confidence, complicates validation, and hinders operational adoption, particularly in policy and emergency management contexts where explainability is essential. Third, computational and infrastructural demands pose practical barriers. Processing large-scale geospatial datasets and supporting near-real-time flood monitoring require substantial computational resources [33]. Limited access to high-performance computing infrastructure can restrict scalability, especially in developing regions where flood risk is often highest. Fourth, integration and interoperability challenges arise when combining heterogeneous data sources, such as satellite imagery, *in situ* hydrological measurements, Internet of Things (IoT) sensors [129], and ancillary socioeconomic information [130]. Differences in spatial resolution, temporal frequency, and data formats complicate seamless integration into operational decision-support systems. Fifth, ethical, privacy, and governance considerations remain underdeveloped [24]. The growing use of sensor networks and citizen-sourced data raises concerns related to data ownership, privacy protection, and responsible data governance, particularly when AI-generated flood assessments inform high-stakes emergency responses. Finally, limited spatial reasoning and physical grounding in many AI systems remain core scientific challenges [98]. Although current models excel at pattern recognition, they often lack an explicit understanding of hydrological processes and spatial dependencies, which can result in physically inconsistent or contextually misleading outputs.

Despite these challenges, the review identifies several promising opportunities for advancing AI-driven flood mapping and modelling. First, enhanced flood prediction and risk assessment can be achieved by combining GeoAI with explainable AI techniques, enabling models to produce both accurate spatial outputs and interpretable insights that clarify the drivers of flood risk. Such capabilities support more informed and actionable decision-making. Second, multi-source data fusion within GeoAI frameworks allows the integration of remote sensing data, IoT observations, hydrological records, and ancillary datasets to generate dynamic, high-resolution flood maps. This capability strengthens early warning systems and enables continuous model updating as new data becomes available. Third, automation and decision support represent key advantages of AI-driven systems. Automated generation of flood maps, analytical summaries, and scenario-based assessments can reduce human workload, accelerate response times, and improve situational awareness during flood events. Fourth, the scalability and transferability of AI models offer significant potential. Techniques such as transfer learning enable models trained in data-rich regions to be adapted to data-scarce environments, supporting broader global application and alignment with international disaster risk reduction frameworks, including the Sendai Framework [75, 76]. Fifth, interdisciplinary collaboration and capacity building are strengthened through the convergence of AI, geospatial sciences, and disaster management. Open-access tools, training programs, and collaborative platforms promote knowledge exchange and enhance global capacity for AI-enabled flood risk assessment. Finally, advancing research frontiers in GeoAI opens pathways toward more adaptive, interactive, and scenario-driven flood analysis, bridging the gap between computational intelligence and societal impact.

Nevertheless, integrating multi-scale geospatial datasets, real-time sensor streams, and community-informed data into AI-driven frameworks offers a pathway toward more adaptive, transparent, and resilient flood management systems. When coupled with robust model monitoring, ethical governance, and alignment with climate policy and Sustainable Development Goal (SDG) frameworks, these approaches not only enhance predictive performance but also strengthen societal resilience, accountability, and public awareness, paving the way for more sustainable and inclusive disaster risk reduction.

3.2. Recommendations

Despite their strong potential, current GeoAI- and GPT-enabled flood mapping systems remain constrained by several critical limitations. First, data constraints persist, as the limited availability of high-resolution, multi-temporal datasets and a strong dependence on historical flood records reduce model robustness when confronted with unprecedented or compound extreme events. Second, model generalization remains challenging; deep learning models that perform well in one region often underperform when transferred to areas with different topographic characteristics, land-use patterns, or climatic conditions. Third, computational demands pose a significant barrier, as resource-intensive data processing and model training restrict near-real-time operational deployment, particularly in developing and resource-limited regions. Fourth, limited spatial awareness remains an issue, as GPT-based models [95] require substantial domain-specific adaptation to interpret hydrological processes and complex spatial relationships accurately. In addition to these technical challenges, ethical and governance concerns are increasingly prominent. The integration of citizen-sourced information and sensor-based data requires careful consideration of privacy, transparency, and accountability to ensure responsible use and to prevent the misuse or misinterpretation of AI-generated flood predictions.

To address the above limitations and unlock the full potential of next-generation geospatial intelligence, this study advances several interrelated recommendations. First, data integration and quality enhancement should be prioritized by developing standardized, high-resolution, and multi-source geospatial datasets. The synergistic use of satellite imagery, Light Detection and Ranging (LiDAR), IoT sensors, and crowdsourced information can substantially improve spatiotemporal resolution and model robustness. In parallel, advanced techniques for harmonizing heterogeneous datasets and imputing missing values are essential to ensure data consistency and reliability. Second, domain-specific adaptation of AI models is critical. Fine-tuning models for spatial reasoning and embedding physical hydrological constraints can bridge the gap between data-driven intelligence and process-based understanding, enabling analyses that are both accurate and operationally meaningful. Third, the development of explainable and transparent models is necessary to support stakeholder trust. Incorporating interpretability mechanisms enables decision-makers to understand model behaviour, assess uncertainty, and confidently integrate AI outputs into emergency response and planning workflows. Fourth, scalability and computational efficiency must be addressed through lightweight model architectures and deployment on cloud and edge computing platforms. Strategies such as model compression and distributed computing can facilitate near-real-time flood prediction, particularly in resource-constrained settings. Fifth, interdisciplinary collaboration and capacity building are essential. Strong partnerships among AI researchers, geospatial scientists, hydrologists, and policymakers, supported by training programs and open-access tools, can strengthen global capabilities in AI-driven flood management [91]. Finally, climate-resilient and policy-integrated modeling frameworks should incorporate climate projections, land-use dynamics, and socioeconomic vulnerability indicators [130]. Adaptive systems that continuously learn from new data streams can improve preparedness for extreme events and support long-term resilience planning. Embedding AI-driven flood mapping within governance structures and emergency protocols ensures that analytical insights translate into effective interventions, from evacuation planning to recovery strategies.

Beyond technical advances, engaging local communities, responsibly leveraging citizen-sourced data, and enhancing public awareness are vital complements. Together, these efforts can ensure that future flood mapping frameworks are not only scientifically robust but also socially resilient, ethically grounded, and actionable in real-world disaster management contexts.

4. Conclusion and Future Direction

Floods remain among the most destructive natural hazards worldwide, threatening human lives, infrastructure, ecosystems, and national economies. In response, flood mapping and modeling have evolved alongside advances in geospatial technologies, shifting from static cartographic representations to dynamic, predictive, and increasingly near-real-time analytical systems. The integration of artificial intelligence with geospatial intelligence has been central to this transformation, substantially enhancing both the spatial detail and temporal responsiveness of flood risk assessments. Within this rapidly advancing landscape, GeoAI, through the integration of AI, GIS, and Earth observation technologies, has emerged as a powerful enabler of more precise flood modeling, simulation, and management. However, floods are not solely hydrological phenomena; they are complex spatiotemporal processes shaped by interactions among environmental conditions, built environments, and socioeconomic exposure. The synthesis of more than 130 reviewed studies indicates that next-generation flood mapping must therefore extend beyond predictive accuracy to become intelligent, adaptive, and interoperable, capable of integrating multi-source data streams, automating analysis, and translating outputs into actionable insights.

Recent research trends indicate a growing reliance on advanced AI-driven methods to improve flood-susceptibility mapping, inundation modeling, and decision support. Machine learning, ensemble methods, deep learning, and hybrid frameworks have demonstrated clear advantages in capturing nonlinear relationships and improving predictive performance. Yet, the integration of large-scale language-based AI architectures into hydrological research remains limited, revealing a notable gap in current practice [131, 132]. While conventional AI models excel at numerical prediction and spatial classification, language-driven AI offers complementary potential by enhancing human-machine interaction, automating interpretation and reporting, and enabling natural language exploration of complex geospatial information. This approach opens new possibilities for rethinking flood analysis as a collaborative process in which computational intelligence and human reasoning are more closely aligned.

To address this gap, this study suggests elaborating on the conceptual SATGPT [91] framework and LLMs-GPT [96, 97] as a reference point for future research. By coupling GeoAI-driven spatial analytics with natural language interaction, the framework aims to improve accessibility, interpretability, and automation in flood mapping and hydrological analysis. In practical terms, such an approach enables users to query, analyze, and visualize flood information using intuitive language, thereby narrowing the divide between advanced geospatial computation and decision-making needs. More broadly, the convergence of GeoAI and language-driven AI has the potential to redefine how flood risks are assessed, communicated, and acted upon. If adequately adapted for geospatial reasoning, these systems could summarize satellite observations, delineate flood extents, and generate decision-ready impact assessments in near real time, transforming static flood maps into adaptive, responsive decision-support platforms.

At the same time, these opportunities are accompanied by substantial challenges. Progress toward AI-driven flood mapping is constrained by data governance issues, privacy concerns, interoperability limitations, and unequal access to geospatial infrastructure, particularly in developing regions. In addition, language-based AI models [131, 133] remain limited in their intrinsic understanding of spatial-temporal dynamics, hydrological connectivity, uncertainty, and physical process representation. Overcoming these constraints requires coordinated efforts to strengthen geospatial data governance, standardize data-sharing practices, and invest in equitable capacity building. Advancing spatially aware, transparent, and explainable AI frameworks is essential if such systems are to be trusted in high-stakes disaster management contexts.

Looking ahead, the future of flood mapping will be shaped by the integration of real-time data streams, predictive modeling, and human-AI collaboration. Continuous inputs from satellites, UAVs, IoT sensors [129], and participatory data sources will increasingly feed adaptive AI systems capable of monitoring and forecasting floods across scales. Emerging paradigms such as federated learning may further enhance global flood prediction while preserving data sovereignty and privacy. Achieving long-term flood resilience will depend not only on technological innovation but also on embedding GeoAI-driven capabilities within governance structures, emergency protocols, and community engagement processes. Open-access data, interoperable platforms, and transparent AI pipelines will form the foundation of this transition.

Ultimately, the conceptualization of SATGPT [91] and similar studies [97, 131, 132] represents a meaningful step toward integrating geospatial analytics with intuitive human interaction for intelligent flood management. Beyond a technical contribution, it reflects a broader paradigm shift toward adaptive, collaborative, and decision-oriented geospatial systems. Addressing remaining challenges, particularly in spatial reasoning, data fusion, and ethical governance, will define the next phase of research. If successfully realized, such frameworks can support resilient, data-informed disaster governance, ensuring that advances in GeoAI translate into practical, equitable, and sustainable flood risk reduction.

Author Contributions

V.I.: Methodology; Formal analysis; Data curation; Writing—review & editing; Validation; Visualization; Project administration. M.S.: Conceptualization; Methodology; Investigations; Formal analysis; Data curation; Writing—review & editing; Validation; Visualization; Project administration. S.P.: Conceptualization; Methodology; Investigations; Writing original draft; Formal analysis; Writing—review & editing; Validation; Supervision; Visualization; Project administration. M.A.: Methodology; Investigations; Validation; Visualization.

Funding

This research received no external funding. All work was conducted as part of independent academic collaboration among the contributing authors.

Informed Consent Statement

Not applicable. This study did not involve human participants, human data, or identifiable personal information; therefore, informed consent was not required.

Data Availability Statement

Data is available upon request.

Acknowledgments

We appreciate the Institute of Artificial Intelligence at Shaoxing University for its collaboration and scientific support.

Conflicts of Interest

The authors declare no conflicts of interest.

Use of AI and AI-assisted Technologies

The authors declare that ChatGPT was used in the manuscript to check the grammar and English.

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