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Artificial Intelligence Approaches for Flood Risk Assessment: A Literature Review

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Abstract

Floods are among the most destructive and frequent natural hazards globally, and recent advances in artificial intelligence (AI) offer significant opportunities to improve prediction, real-time monitoring, and flood mapping. In this review, we synthesize and compare AI-based approaches applied to flood risk management, encompassing convolutional neural networks (CNNs), deep neural networks (DNNs), recurrent models (LSTM and RNN), physics-informed architectures, multimodal systems, and IoT-integrated frameworks. These models leverage diverse data sources, including satellite imagery, UAV observations, social media, hydrological sensors, and remote sensing products, to enhance forecasting accuracy and situational awareness. We also examine non-deep-learning methods such as Random Forests, XGBoost, and regression-based models that remain effective in data-scarce environments. Drawing on 45 peer-reviewed studies published between 2021 and 2025, we systematically compare these techniques across three operational domains: flood prediction and risk assessment, real-time monitoring and response, and flood mapping and susceptibility analysis. Our analysis highlights persistent challenges including limited model generalizability, absence of standardized benchmarks, and insufficient interpretability, and identifies strategic directions for developing robust, scalable, and explainable AI systems for flood risk management under evolving climate conditions.

Keywords
Flood risk assessment, Artificial intelligence, Deep learning, Convolutional neural network and Flood prediction.

1. Introduction
Floods are among the most damaging and frequent natural disasters globally, affecting millions of people and causing billions of dollars in damage each year. Recent events illustrate the growing urgency of effective flood prediction and management: in July 2025 alone, extreme rainfall caused catastrophic flooding across the United States, submerging urban infrastructure, disrupting transportation networks, and resulting in significant loss of life across Texas, Chicago, North Carolina, New York City, and Kansas City. Such events are becoming more frequent and severe due to intensifying climate change, urban expansion into flood-prone areas, and shifting precipitation patterns (Luccioni et al. 2021). The societal and economic costs of flooding call attention to the need for improved warning systems, accurate flood mapping, and rapid response capabilities (Lin et al. 2023a).

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Conventional flood prediction approaches, including hydrological and hydraulic models, rely on accurate rainfall and river gauge data alongside precisely calibrated parameters (Chen et al. 2023). While effective for decades, these models tend to underperform in areas with limited observation networks, during extreme events where conditions deviate from historical patterns, and when real-time analysis is urgently needed. They frequently oversimplify complex natural processes such as evaporation and infiltration, and their high computational cost limits applicability in large-scale or time-sensitive scenarios. These limitations are especially pronounced in urban environments, where data demands are higher and flood vulnerability is greater (Yang et al. 2024).

Artificial intelligence (AI) has emerged as a transformative approach to address these gaps. By employing machine learning (ML) and deep learning (DL) techniques, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models, AI systems can incorporate diverse data sources ranging from satellite imagery and hydrological sensors to social media and UAV observations (Shi et al. 2025). These models enable more accurate and efficient forecasting, strengthen early warning systems, enhance flood mapping in data-scarce regions, and support real-time situational awareness during active flood events (Jones et al. 2023).

This review synthesizes recent AI-driven flood research across three operational domains: flood prediction and risk assessment, real-time monitoring and response, and flood mapping and susceptibility analysis. By systematically comparing deep learning architectures (CNNs, DNNs, LSTMs, hybrid, and physics-informed models), ensemble methods (Random Forest, XGBoost, Gradient Boosting), and IoT-integrated and multimodal frameworks, this review identifies methodological trends, model strengths and limitations, and practical deployment considerations. In doing so, it provides researchers, practitioners, and policymakers with a consolidated and operationally relevant reference for developing robust, interpretable, and scalable AI systems for flood risk management under evolving climate conditions.

2. Literature Review

Related Reviews: Strengths and Weaknesses is presented below in Table 1.

Table 1. Related Reviews: Strengths and Weaknesses

Citation	What this review offers	What this review lacks
(Liu et al. 2024)	Offers insight into multiple dimensions including flood types, AI models, spatial scales, input data, and applications. Proposes future research pathways to harness AI's potential for adaptive flood risk management.	Not recent; does not present new empirical results. Does not focus on operational implementation challenges in real-world systems.
(Jones et al. 2023)	Addresses the role of AI/ML in quantifying climate change-related hazards, impacts, and risks. Provides examples from flood-related applications and discusses challenges in alternative methods.	Not recent; does not provide detailed performance comparisons for specific AI models in flood applications. Focuses broadly on climate impact modelling.
(Bhanye 2025)	Encompasses AI applications in urban flood adaptation across forecasting, vulnerability assessment, planning, response, and recovery. Addresses governance and justice challenges.	Limited focus on operational implementation of AI tools in real-world disaster management systems. Does not provide detailed empirical metrics or comparisons of specific AI models.
(Chukwu 2025)	Utilises structured search across Scopus, Web of Science, IEEE, Springer, and ScienceDirect. Groups 64 eligible studies into four thematic domains relevant to flood risk under climate change.	Does not provide detailed quantitative comparisons of specific AI model performance. Lacks focus on computing efficiency or deployment constraints for XAI systems in practice.
(Farzad et al. 2025)	Comprehensive review of global research on AI methods for flood susceptibility prediction, covering parameters, performance metrics, study areas, and data sources. Notes geographic emphasis on Asian countries.	Does not provide detailed empirical comparison of specific model performance across studies. Limited focus on real-time flood prediction or operational early warning systems.
(Maddodi et al. 2026)	Discusses AI-driven flood and drought risk management, integrating machine learning, neural networks, and fuzzy logic systems. Identifies key	Somewhat broad; may dilute focus on flood-specific methodologies. Does not provide standardized guidance on model selection or

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Citation	What this review offers	What this review lacks
	challenges such as dataset availability and computational efficiency.	comparison across different AI frameworks.

While existing reviews have examined artificial intelligence applications in flood susceptibility mapping, climate impact modeling, explainable AI, disaster governance, and integrated flood and drought systems, most focus on a single dimension of flood risk management or emphasize either technical performance or socio-institutional considerations in isolation. **Table 1** describes 6 related reviews and their contributions to machine learning development regarding flood risk. Several surveys concentrate exclusively on flood susceptibility prediction, while others address broader climate hazards without providing detailed synthesis of operational flood modeling approaches. Additionally, prior reviews such as (Farzad et al. 2025) often lack integrated comparison across prediction models and details on real-time monitoring. (Jones et al. 2023) and (Liu et al. 2024) both do not provide recent empirical results. In contrast, this review provides a consolidated and up-to-date synthesis of AI-driven flood research across prediction, real-time systems, and flood mapping, encompassing deep learning, ensemble models, IoT-integrated platforms, multimodal vision language systems, and physics-informed approaches. By analyzing methodological trends, data sources, model strengths and limitations, and practical deployment considerations within a unified framework, this study offers a more comprehensive and operationally relevant perspective on AI-enabled flood risk management. Consequently, it delivers a clearer comparative understanding of current advancements and identifies strategic directions for developing robust, interpretable, and scalable flood management systems under evolving climate conditions.

3 Methods

3.1 Review Design and Scope

This study follows a systematic literature review methodology to examine the application of artificial intelligence, including machine learning (ML) and deep learning (DL), to three operational domains of flood risk management: flood prediction and risk assessment, real-time monitoring and response, and flood mapping and susceptibility analysis. The review was structured around four sequential phases, illustrated in **Figure 1**: (1) search and identification, (2) screening and eligibility assessment, (3) data extraction and coding, and (4) synthesis and classification. This phased approach ensures transparency, reproducibility, and analytical rigor across all stages of the review process.

Four-phase systematic review pipeline from initial database search to final domain classification. Study counts reflect the progression from 550 candidate records to 45 eligible studies organized across three operational domains.

3.2 Search Strategy and Article Identification

Articles were identified through a structured search of Google Scholar, conducted in October 2025. Google Scholar was selected for its broad coverage of interdisciplinary literature spanning engineering, hydrology, remote sensing, and computer science. The search applied Boolean operators (AND, OR) combined with targeted keyword phrases to capture the range of AI applications relevant to flood risk. The primary search strings included: "US flood and AI," "CNN flood prediction," "Deep learning flood prediction," "Deep Neural Network flood prediction," "flood prediction convolutional neural network," and "US flood forecasting and AI." To ensure currency and relevance, results were restricted to English-language, peer-reviewed articles published between 1 January 2021 and 31 December 2025. This five-year window was chosen to capture the most recent advances in deep learning and machine learning applied to flood management, while excluding earlier work already addressed in prior reviews.

3.3 Screening and Eligibility Assessment

The initial search returned 550 records. After applying title and abstract screening for topic relevance, 76 articles were retained for full-text review. Following deduplication (23 removed), 53 unique records underwent detailed eligibility assessment. Studies were evaluated against the criteria presented in **Table 2**. Eight articles were subsequently excluded: four because full texts were inaccessible, three because they reported no original AI model evaluation, and one because it focused exclusively on precipitation forecasting with no flood-specific output. This yielded a final corpus of 45 peer-reviewed studies.

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Table 2. Inclusion and Exclusion Criteria for Article Selection

Inclusion Criteria	**Exclusion Criteria**
a) Publication date between 1 January 2021 and 2025	a) The publication was published before 1 January 2021
b) Peer-reviewed article (non-peer reviewed texts excluded)	b) The publication was a literature review or perspective paper
c) Reported the use of ML/DL models for flood prediction, mapping, or real-time risk assessment	c) The complete text was not accessible or did not report original model evaluation

3.4 Data Extraction and Coding

For each of the 45 eligible articles, the following information was systematically extracted into a structured spreadsheet: study objectives, geographic location and spatial scale, AI model type and architecture, input data sources, reported performance metrics (e.g., accuracy, RMSE, NSE, AUC, R^2), and key limitations identified by the authors. Where multiple metrics were reported, the primary performance indicator was recorded alongside supplementary measures. Studies that reported qualitative rather than quantitative outcomes were coded descriptively.

3.5 Classification Framework and Analytical Scope

Following extraction, studies were classified into three operational domains aligned with the primary function of the AI model under review. **Figure 2** illustrates the analytical framework used to organize this classification, mapping AI model families and input data types onto the three flood risk domains. Flood prediction and risk assessment (n = 27) encompasses models designed to forecast flood occurrence, water levels, or susceptibility ahead of an event. Real-time monitoring and response (n = 14) includes systems that detect, track, or characterize floods during active events using live data streams. Flood mapping and susceptibility analysis (n = 4) covers models that delineate inundated areas or produce spatial risk maps, typically from satellite or aerial imagery. The analysis within each domain focuses on model architecture, data requirements, reported performance, and operational constraints.

Classification framework showing how AI model families and input data types feed into the review scope and are organized across the three flood risk domains. Arrows flow strictly left to right: model architectures and data sources converge at the review corpus (45 studies, 2021–2025) and are then classified into three operational domains.
Study selection process from initial database query to final corpus. Records were progressively filtered through relevance screening, deduplication, and eligibility assessment, yielding 45 studies distributed across three review domains.

4. Results and Discussion

Artificial Intelligence (AI) has transformed flood-related research by introducing advanced modeling techniques that surpass traditional hydrological and hydraulic systems in both their adaptability and their precision. Across recent studies, deep learning (DL) and machine learning (ML) models have been applied to forecast flood events, map flood extents, and assess real-time risks. Models such as Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), Random Forests (RF), and hybrid architectures demonstrate strong capabilities in capturing nonlinear relationships between rainfall, topography, land use, and flood dynamics. While CNNs and DNNs have proven effective in spatial flood mapping through satellite and remote sensing data, RF and other ML-based approaches excel in processing structured datasets like precipitation and soil moisture records. These diverse methods highlight the growing integration of data-driven approaches in flood science, offering both predictive and real-time insights that enhance early warning systems, urban flood planning, and disaster mitigation strategies. In this section, we systematically review and compare these AI-based methodologies, analyzing their applications, strengths, limitations, and contributions to flood prediction, real-time monitoring, and mapping.

4.1 Flood Prediction Models

This section reviews the AI models used for forecasting and early warning systems. Deep learning (DL) models such as CNN, DNN, and LSTM have been widely used to anticipate flood events by learning temporal and spatial rainfall patterns, river discharge data, and soil moisture dynamics. Many of these models outperform traditional statistical and hydrological approaches, particularly in handling nonlinear relationships and integrating multiple data

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sources. For instance, studies applying CNN and hybrid DNN frameworks have achieved high accuracy in predicting flood probabilities and water levels. However, these models depend heavily on the availability of quality input data and may perform inconsistently in regions with limited observations or shifting climatic trends. **Figure 1** summarizes the reported performance of flood prediction models across 19 studies, organized by model type.

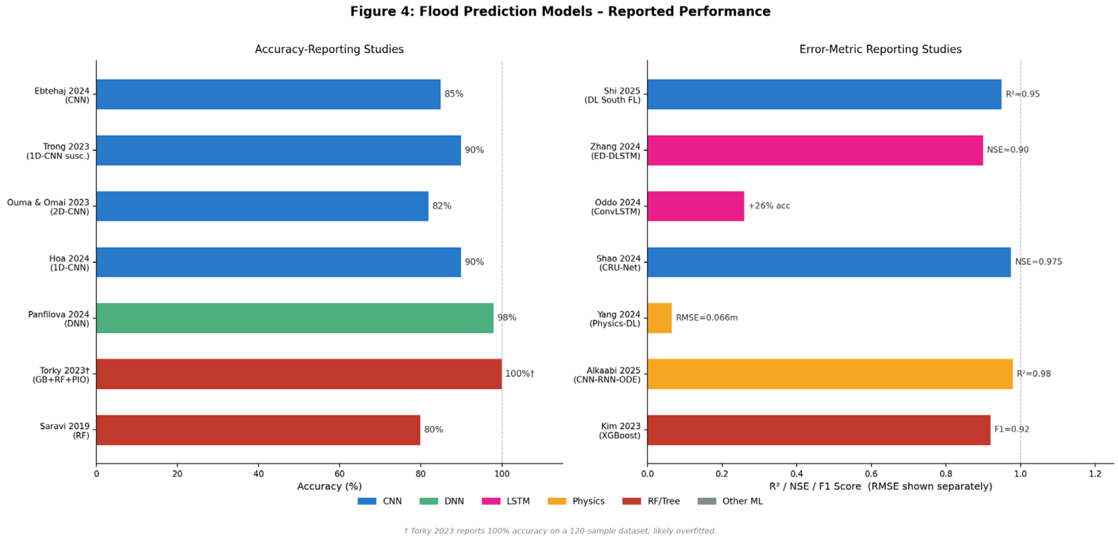

Figure 1. Reported performance of flood prediction models across reviewed studies. Left panel shows accuracy-reporting studies; right panel shows studies reporting R^2, NSE, or F1 scores. Color indicates model family. RF/Tree appear *to have best overall performance*

4.1.1 Convolutional Neural Network (CNN)-Based Models

Convolutional Neural Networks (CNNs) are widely applied in flood research because of their ability to extract spatial features from imagery and gridded data, making them effective for both mapping and prediction tasks. (Ouma and Omai 2023) use a 2D CNN for urban flood mapping, achieving 82.5 percent accuracy, while (Kabir et al. 2020) apply a deep CNN for real-time forecasting using hydrometric and topographic inputs. CNNs have also been used for short to medium-term prediction. (Windheuser et al. 2023) combine CNNs with image segmentation to forecast flood stages up to 48 hours ahead. Beyond prediction, (Luccioni et al. 2021) show that CNN-generated flood visualizations can enhance public awareness of climate risks. Comparative work by (Ebtehaj and Bonakdari 2024) finds that CNNs outperform LSTMs for short-term forecasting due to computational efficiency and stronger spatial learning. Applications span multiple regions: (Hoa et al. 2024) achieve 90.2 percent accuracy in flash-flood prediction with a 1D CNN, and (Shao et al. 2024) report high precision using the CNN-based CRU-Net in urban flood modeling (RMSE = 0.054 m, NSE = 0.975). Overall, CNN studies consistently show strong spatial predictive skill, fast computation, and adaptability across diverse flood scenarios.

4.1.2 Deep Neural Network (DNN) Models

Deep Neural Networks (DNNs) are widely used in flood research due to their ability to model complex nonlinear relationships in hydrologic variables such as rainfall, discharge, and soil moisture. In urban settings, (Panfilova et al. 2024) integrate a DNN with GIS-based spatial data to generate detailed urban flood risk maps, demonstrating the model's strength in capturing heterogeneous environmental factors. Extending DNN applications to meteorological forecasting, (Munandar et al. 2024) combine a GSTARIMA statistical model with a DNN to improve rainfall prediction in Indonesia, showing that hybridizing nonlinear learning with time-series structures enhances forecasting accuracy. Similarly, (Kim et al. 2023) report that DNN models outperform alternative machine learning approaches for predicting floodwater levels in the Philippines, highlighting their reliability in data-rich hydrological contexts. Collectively, these studies demonstrate that DNNs consistently perform well when capturing complex hydrologic interactions for flood risk assessment and prediction.

4.1.3 Recurrent Models: LSTM, RNN, and Hybrid CNN-LSTM Approaches

Recurrent models capture temporal dependencies, making them well-suited for time-series flood forecasting (e.g., rainfall or river discharge over time). Several studies demonstrate their advantages for spatiotemporal flood prediction. (Giezendanner et al. 2023) combine CNN and LSTM components to improve flood mapping in

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Bangladesh by integrating spatial features with temporal dynamics. Similarly, (Shahabi and Tahvildari 2024) employ a CNN-LSTM model to predict water levels in Chesapeake Bay using NOAA tidal and wind observations, improving multi-step forecasting. Hybrid approaches also show strong performance. (Oddo et al. 2024) introduce a ConvLSTM model that predicts flash-flood stream stages with a 26 percent accuracy improvement, while (Zhang et al. 2024) propose an encoder-decoder double-layer LSTM capable of forecasting floods in both gauged and ungauged basins globally. Comparative analyses reinforce these strengths. (Ebtehaj and Bonakdari 2024) find that LSTMs outperform CNNs for longer-term precipitation prediction due to better memory of temporal sequences, and (Shi et al. 2025) show that recurrent and deep learning models (MLP, RNN, CNN, LSTM, RCNN) generally exceed physics-based hydrological models in both speed and accuracy. Overall, recurrent architectures consistently excel when temporal dynamics are central to flood forecasting.

4.1.4 Physics-Informed and Hybrid Deep Learning Models

Recent work tends to incorporate hydrological principles and physical constraints into deep learning architectures to improve model reliability, stability, and interpretability in flood prediction. (Radfar et al. 2025) introduce ALPINE: a physics-informed DL emulator that embeds mass-conservation and momentum equations to enhance physical consistency. In urban environments, (Yang et al. 2024) apply a physics-guided DL framework for flood induction mapping, achieving low error (RMSE = 0.066 m) by integrating hydraulic reasoning into the network. Physical validation has also been advanced through remote sensing. (Masafu and Williams 2024) combine SegFormer and CNN architectures with satellite-derived flow observations (LSPIV) to estimate flood extents while evaluating uncertainty from both the model and sensor data. Hybrid formulations continue to evolve. (Alkaabi et al. 2025) develop a CNN-RNN-Neural ODE system for flash-flood runoff prediction, incorporating differential equation constraints and achieving high accuracy (R^2 = 0.98; PBIAS = -8.38). Across these studies, the integration of physical laws into DL offers more stable, explainable, and generalizable flood modeling.

4.1.5 Random Forest (RF) and Other Tree-Based Models

Tree-based ensemble models, including Random Forest (RF), Gradient Boosting (GB), and XGBoost (XGB), remain widely used in flood research because they handle structured environmental data effectively and offer interpretable feature importance insights. (Valavanidis 2024) demonstrates, at the global scale, that RF can predict flood occurrence using GloFAS hydrology, MODIS satellite observations, and ERA5 climate reanalysis, highlighting its strength across heterogeneous inputs. Regionally, (Demissie et al. 2024) show that combining RF with XGB improves flood susceptibility mapping and outperforms other machine-learning classifiers. RF has also been applied to categorical flood classification. (Saravi et al. 2019) use FEMA and NOAA datasets to distinguish flash, coastal, and lakeshore floods with over 80 percent accuracy. Model ensembles continue to show strong results: (Torky et al. 2023) blend GB and RF with parameter optimization (PIO), achieving 100 percent accuracy in flood prediction for Kerala, India. Finally, (Kim et al. 2023) apply both XGBoost and RF for flood-risk classification, reporting that XGBoost yields the highest performance (F1 = 0.92). Overall, RF and related tree-based models offer robustness, interpretability, and strong predictive capability across diverse flood applications.

4.1.6 Other Machine Learning and Statistical Approaches

Several studies apply machine learning and statistical approaches outside of deep learning to support efficient and data-driven flood forecasting. In South Korea, (Ahmed et al. 2022) use Locally Linear Regression for short-term streamflow prediction and show that simple regression techniques can perform well when high-frequency hydrological data are available. Broader comparative work by (Adikari et al. 2021) evaluates CNN, WANFIS, and multiple hybrid statistical models for flood and drought forecasting across different climate regions and finds that model performance varies significantly with regional hydrologic behavior. In West Africa, (Nearing et al. 2023) integrate GloFAS outputs with artificial neural networks and satellite imagery to improve flood prediction in data-scarce areas, demonstrating the value of combining global reanalysis products with machine learning. Finally, (Jones et al. 2023) discuss how regression methods, surrogate modeling, and geospatial learning contribute to climate impact prediction and emphasize the growing role of hybrid statistical and AI frameworks in flood modeling. These approaches collectively show that statistical and machine learning techniques remain effective tools, particularly when computational efficiency or limited data availability are key constraints.

4.2 Real-Time Models

Real-time flood research focuses on rapid detection, monitoring, and response during active or emerging flood events. These approaches integrate sensor networks, IoT devices, UAV imagery, satellite observations, and multimodal AI systems to enable fast, actionable flood intelligence. Many recent studies employ CNNs, LSTMs, hybrid CNN-LSTM models, Transformers, and multimodal architectures to process diverse real-time data streams. Collectively, these models emphasize timeliness, rapid computation, and adaptability, enabling operational flood assessment under uncertain and dynamic conditions. **Figure 2** summarizes performance across the 14 real-time studies reviewed, highlighting both numerically reported and qualitatively described outcomes by model type.

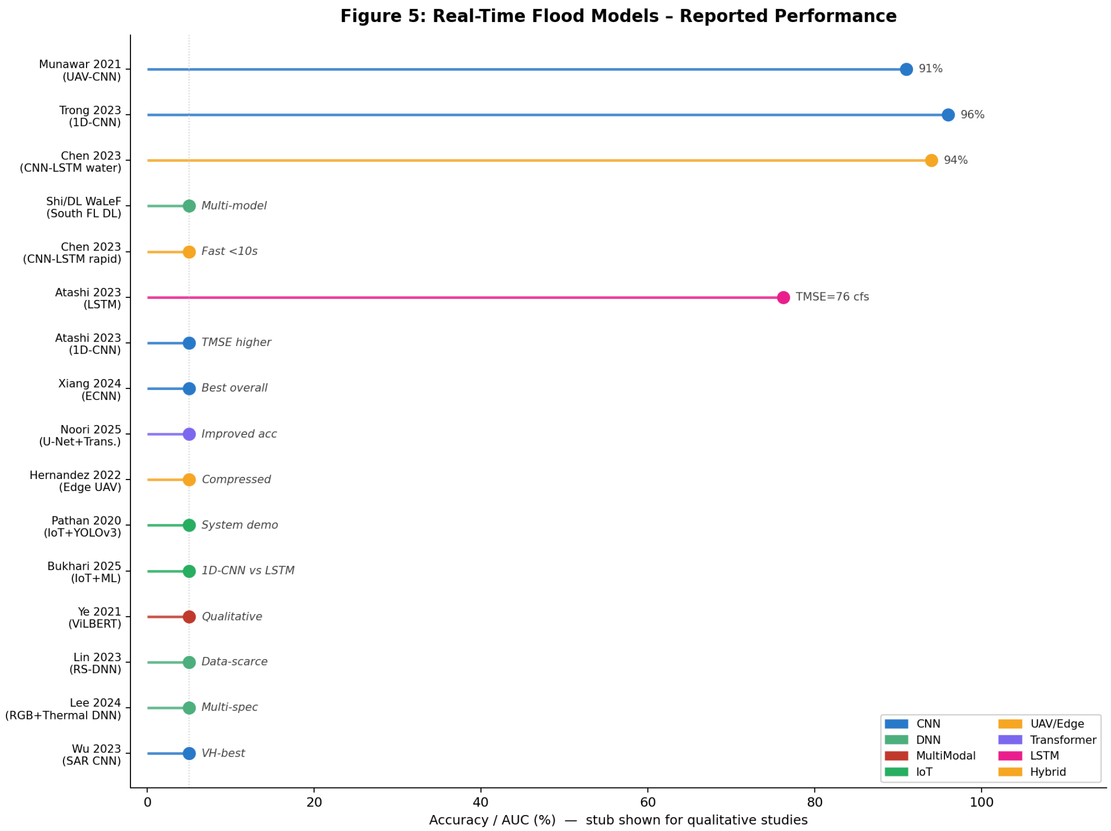

Figure 2. Reported performance of real-time flood monitoring models. Left panel shows studies with numeric accuracy or AUC results; right panel lists all studies with their reported metric or qualitative finding. Color indicates model architecture. CNN appears to have best overall model performance

4.2.1 IoT-Integrated and Sensor-Based Models

Real-time sensing remains foundational for operational flood monitoring. (Pathan et al. 2020) develop an IoT-enabled flood monitoring and rescue system that uses water-level, humidity, pressure, and temperature sensors, along with drone-based YOLOv3 human detection, to support emergency response in India. Expanding IoT capabilities, (Bukhari et al. 2025) integrate sensor networks with machine-learning models, comparing 1D CNN and M-LSTM architectures on a multi-station IoT prototype involving water, repeater, and siren stations. These works demonstrate how IoT infrastructure paired with AI enhances real-time situational awareness and flood response coordination.

4.2.2 Vision Language and Multimodal Models

Multimodal systems fuse visual and textual information for rapid event assessment. (Ye et al. 2021) introduce a ViLBERT-based vision-language framework enhanced with a novel LSVRU module to classify U.S. flood events using satellite imagery combined with textual data from tweets and news reports. Trained on FEMA datasets, the model shows the strength of multimodal fusion for assessing flood severity and improving national-scale disaster monitoring.

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4.2.3 Deep Neural Networks (DNN) and Region-Stable Models
DNN-based real-time systems increasingly incorporate social sensing and thermal imagery. (Lin et al. 2023b) propose a Region-Stable DNN (RS-DNN) that integrates social media (Twitter), remote sensing, and GIS data to generate flood-risk maps that generalize across data-scarce regions. Meanwhile, (Lee et al. 2024) fuse RGB and thermal (LWIR) surveillance videos within a DNN segmentation pipeline to improve flood extent detection under poor lighting or cloud-affected conditions. These approaches highlight the versatility of DNNs for real-time mapping when traditional imagery or datasets are limited.

4.2.4 CNN-Based Models
CNN architectures remain widely used for fast flood detection and susceptibility assessment. (Trong et al. 2023) apply a 1D-CNN to fluvial flood susceptibility mapping in Vietnam, achieving an AUC of 0.96 and surpassing classical models such as DeepNN, SVM, and Logistic Regression. For large-scale real-time observation, (Wu et al. 2023) employ CNNs with SAR imaging in the Yangtze River Basin, showing that VH polarization yields the highest detection accuracy and that weakly labeled training data improve performance. UAV-enabled CNN pipelines also demonstrate strong real-time capabilities. (Munawar et al. 2021) use drone imagery to detect flood-affected infrastructure in Pakistan's Indus River region with approximately 91 percent accuracy.

4.2.5 Comparative CNN and LSTM Models
Comparative studies examine temporal learning versus spatial learning in real-time contexts. (Atashi et al. 2023) compare 1D-CNN and LSTM models using decades of USGS streamflow data for Grand Forks, finding that LSTM achieves substantially lower error (TMSE = 76.23 cfs) than 1D-CNN. Similarly, (Xiang et al. 2024) propose an Efficient CNN (ECNN) for flood forecasting in the Lushui Basin and show that it outperforms LSTM, CNN, and hybrid LSTM-CNN architectures, with Grad-CAM visualizations improving interpretability. Hybrid models continue to advance rapid prediction. (Chen et al. 2023) introduce a CNN-LSTM system that estimates urban flood depth in under 10 seconds, achieving under 6.5 percent error through the integration of rainfall, land use, terrain, and drainage data.

4.2.6 Transformer and Hybrid Architectures
Transformer-based architectures are emerging for fast flood detection. (Noori et al. 2025) combine CNN U-Net with a Transformer encoder for real-time flash-flood mapping using Sentinel-1 VH imagery. Their hybrid model improves accuracy and speed over conventional CNN models, underscoring the potential of attention mechanisms for rapid disaster assessment.

4.2.7 UAV-Based and Edge-Computing Models
Edge-optimized models enable real-time inference directly on UAVs or field devices. (Hernández et al. 2022) evaluate PSPNet, DeepLabV3, and U-Net deployed on Jetson edge hardware using the FloodNet dataset, demonstrating accurate segmentation while transmitting only compressed masks. This strategy reduces bandwidth demands while maintaining precision, which is crucial for emergency operations during network disruptions.

4.2.8 Review and Foundational Studies
Foundational literature provides context for the progression of real-time flood monitoring techniques. (Zanchetta and Coulibaly 2020) synthesize developments in rainfall-induced flash-flood forecasting, emphasizing atmospheric precursors, multisource data assimilation, IoT integration, and uncertainty estimation. This body of work informs many of the real-time AI frameworks adopted in recent studies.

4.3 Flood Mapping
Flood mapping research focuses on rapidly identifying inundated areas using satellite imagery, UAV data, social sensing, and machine-learning-based classification. These models provide near-real-time assessments of flood extent to support emergency response, especially in environments with limited sensor infrastructure. Deep learning approaches such as CNNs and image segmentation networks are widely adopted for spatial feature extraction, while ensemble and classical machine-learning models contribute robust multispectral classification capabilities. Many studies emphasize deployable, low-cost, or data-scarce solutions, reflecting the need for accessible operational mapping tools across diverse geographic contexts. **Figure 3** summarizes the performance of the four flood mapping studies reviewed.

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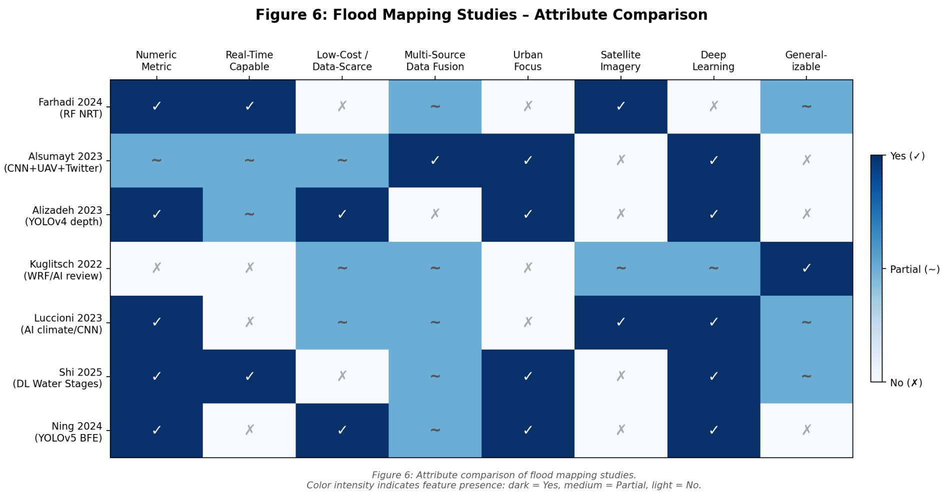

Figure 3. Reported performance of flood mapping models. Bar length reflects numeric accuracy where reported; qualitative findings are annotated for studies without numeric metrics. Color indicates model family.

4.3.1 CNN and Deep Learning Models

Deep learning-based image analysis continues to play a central role in real-time flood mapping. (Alsumayt et al. 2023) present a CNN model that integrates UAV imagery with social media inputs from platforms such as Twitter to detect flooded road segments, enabling rapid, localized flood mapping in urban environments with limited monitoring infrastructure. Extending the use of deep learning for community-level applications, (Alizadeh Kharazi and Behzadan 2023) propose a low-cost approach for estimating urban floodwater depth by using a pretrained YOLOv4 model and standardized stop-sign heights as reference indicators. This method provides an accessible alternative for regions lacking sensors or updated hydrological maps. Together, these studies show how CNN-based systems leverage both airborne imagery and unconventional data sources to improve operational flood mapping.

4.3.2 Machine Learning and Ensemble Models

Machine-learning classifiers also demonstrate strong potential for rapid, multispectral flood detection. (Farhadi et al. 2024) develop a near-real-time satellite-based mapping system that employs a Random Forest classifier to distinguish flooded areas from land, vegetation, and built environments using multi-sensor imagery. The model outperforms SVM and Decision Tree baselines, achieving 90.57 percent accuracy and a Kappa coefficient of 0.89, demonstrating the value of ensemble learning for high-speed flood extent delineation.

4.3.3 Review and Cross-Hazard Perspectives

Broad assessments of AI methods provide context for these mapping developments. (Kuglitsch et al. 2022) review the expanding role of AI and machine learning in disaster risk reduction, highlighting advancements in flood hazard mapping, flash-flood detection, and multisource data integration. The review also outlines challenges related to data bias, computing cost, and transparency, situating flood-mapping models within the wider landscape of operational, AI-driven disaster management.

5. Conclusion

This review has examined 45 studies applying artificial intelligence to flood prediction, real-time monitoring, and flood mapping, offering a consolidated synthesis of the current state of AI-driven flood research. Across all three domains, a clear picture emerges: deep learning and ensemble models consistently outperform traditional hydrological and hydraulic approaches in accuracy, adaptability, and computational efficiency, though each model family carries distinct trade-offs.

In flood prediction, CNN and hybrid CNN-LSTM architectures demonstrated strong spatial and temporal forecasting capability, with physics-informed models like ALPINE offering improved physical consistency and generalizability. LSTM-based models proved especially effective for longer-horizon temporal forecasting, while Random Forest and XGBoost remained competitive in data-scarce or structured-data settings. In real-time

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monitoring, IoT-integrated systems, UAV-enabled pipelines, and multimodal vision language models collectively extended flood intelligence to previously inaccessible environments, though bandwidth and edge-computing constraints remain practical barriers. In flood mapping, CNN-based segmentation and ensemble classifiers achieved high accuracy in near-real-time inundation detection, with low-cost approaches such as YOLOv4-based depth estimation showing promise for regions lacking sensor infrastructure.

Several cross-cutting challenges persist across all three domains. First, most models are trained on region-specific datasets and demonstrate limited generalizability to new geographies or climate regimes, which remains a critical limitation for global flood risk management. Second, the field lacks standardized benchmarks and performance metrics, making rigorous cross-study comparison difficult. Third, model interpretability remains underdeveloped: while Grad-CAM visualizations and physics-informed constraints offer partial transparency, most deep learning systems function as black boxes, limiting trust among emergency managers and policymakers. Finally, real-time integration between prediction, monitoring, and mapping systems remains rare, even though unified pipelines would offer significant operational value.

Future research should prioritize transfer learning and domain adaptation to improve cross-regional model performance, the development of shared flood benchmark datasets, and the integration of explainability methods into operational systems. Closer collaboration between AI researchers and hydrological practitioners will be essential to translate model performance into real-world flood resilience. This review serves as a reference for those seeking to develop, evaluate, or deploy AI solutions for flood risk reduction in an era of increasing climate uncertainty.

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