Review of Machine Learning and Deep Learning Techniques for Flood Forecasting

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Abstract - Natural flood incidents are increasingly threatening urban and peri-urban populations; however, the effectiveness of operational early warning systems is jeopardized by the variety of disparate data, insufficient applicability across regions, and inconsistent evaluation criteria. This paper, through a systematic review of published studies related to AI-based flood prediction in urban areas, specifically studies based on traditional machine learning (ML) methods, deep learning, hybrid physics-ML modelling, and probabilistic models, summarizes the existing body of work. The overall findings demonstrate that satisfactory prediction systems require a multiple-modal pipeline that encompasses different hydrology datasets, historical incident data and numerical weather forecasts. Successful implementation requires extensive feature engineering, with an emphasis on time-series analyses (i.e., lagged fills and rolling statistics) and composite risk indicators. Predictive modelling incorporates robust ensemble methods like XGBoost, with the application of stratified cross-validation and the optimization of thresholds specifically for prioritizing high recall in alerts that pose a safety risk. While reported results in studies indicate good discriminative measures across multiple test datasets, they also allude to continued weaknesses in the space, including ongoing issues related to data heterogeneity, transferability across different basins, and uncertainty calibration, along with a fundamental challenge in establishing robustness.

Key Words: Flood Forecasting; Machine Learning; Deep Learning; Hybrid Modelling; Probabilistic Forecasting; Spatio-Temporal Networks; Generative AI; Diffusion Models; Digital Twins; Flood Susceptibility Mapping; Hydrological Modelling; XGBoost; LSTM; Feature Engineering; Uncertainty Quantification; Operational Resilience

1. INTRODUCTION

The increase in frequency and severity of natural disasters, especially flooding, underscores the need for thoughtful and innovative ways to prepare for disasters. Traditional early warning systems often do not offer good accuracy, real time response, and sensitivity to local areas. Due to the growth of AI and big data, predictive modelling for natural disasters has emerged as a vital area of research. AI systems enable the analysis of large amounts of data quickly and will allow researchers to examine patterns and make predictions using the large volumes of environmental data generated from various sources such as meteorological, hydrological, and satellites. This review focuses on the use of AI in flood prediction, an area with considerable relevance for practice because of its social, economic, and environmental effects. The papers we selected cover a range of approaches: integration of hydrodynamic models, deep learning detection based on synthetic aperture radar (SAR), and multi-step machine learning regression specific to mountainous areas. Each of these research projects contributes in its own way to the growing area of prediction for disaster, while contributing to the body of knowledge on model performance, implementation challenges, and directions for future research.

2. LITERATURE REVIEW

A. Classical Machine Learning

Established machine learning models have been utilized effectively for flood susceptibility mapping and risk assessments. Bagging (random forest), extreme gradient boosting (XGBoost), and logistic regression were the three most commonly used algorithms to develop flood susceptibility models, each incorporating elements of topography, hydrology, and meteorology. With respect to predictive accuracy of the model outcomes, logistic regression outperformed both XGBoost and bagging, and was able to classify the study areas into different risk zones for emergency preparedness and infrastructures.

Nonetheless, traditional models likely have outperformed deep learning and ensemble models because of data availability and the amount of variability in predictive outputs between models rather than being a true superiority of predictive capacity. This presents even more challenges in considering temporal dynamics and complexity of dependencies characteristic of floods.

B. Deep Learning Approaches

Functioning traditional machine learning models have been effectively used in flood susceptibility mapping and flood risk assessments. In terms of algorithm, the three most common approaches to develop flood susceptibility models each utilized principles of topography, hydrology and meteorology, were bagging (random forest), extreme gradient boosting (XGBoost), and logistic regression methods. While logistic regression produced the greatest effectiveness of predictive accuracy of the model outcomes, both bagging and XGBoost did classify the study areas into varying risk zones for emergency preparedness and infrastructures.

Despite the success of traditional models of floods, I suspect they have performed better than deep learning and ensemble models due to a combination data availability and the greater amount of variability in predictive outputs between models, in contrast to the results being truly superior in predictive capacity. This adds further burdensome consideration to evolving temporal dynamics and complexity of dependencies that is inherent to floods.

C. Hybrid and Ensemble Approaches

Hybrid techniques that merge machine learning and principles of physical modelling show high promise. By combining CIO (Central Indian Ocean) mode with machine learning approaches for monsoon rainfall prediction, there is a significant improvement in skill. The prediction period can exceed 15 days by filtering noise at high frequencies and leveraging dynamic relationships. The hybrid method uses important physical laws and the adaptability of data-driven algorithms. Ensemble-based predictions are more trustworthy because they use probabilistic methods to figure out how likely flooding is based on deterministic forecasts made by several ensemble members. Research has used as many as 50 ensemble members to help figure out how uncertain something is. It cannot be overstated how difficult it is to use these methods in a real-time operational setting.

D. Probabilistic and Risk-based Models:

Uncertainty in flood prediction systems can be addressed effectively through techniques based on probabilistic modelling. Probabilistic forecasts of inundation that account for uncertainty regarding rainfall forecasts are critical for an efficient flood early warning system. Diffusion-based runoff models (DRUM) provide a breakthrough in technology, exceeding leading benchmarks by improving nowcasting accuracy for extreme flows in 72.3% of the basins studied, while extending lead times by nearly one day of reliable information.

In the best-case scenario, when precipitation is well quantified, the models achieve increases in recall of 0.3-0.4 and extend early warning lead times by 2.3 days when forecasting for large floods. Areas receiving precipitation-driven floods in the eastern and northwestern United States realize lead time increases of 3-7 days. Nevertheless, the challenges associated with operationalizing these models involve issues of computational complexity and interpretation of estimated uncertainty.

E. Operational and Deployment-focused Studies

Real-time operational deployment accentuates computational efficiency and the capacity of multi-system integration. Data-driven models are advantageous due to their ease of computation and speed of delivery of results and thus can address computational burdens of physically-based numerical models. LSTM networks parameterized by extensive hydraulic simulations present a potential means for rapid deployment and accurate predictions in seconds.

Advanced models ensure operational efficiency while expanding forecast horizons; the AT-Bi LSTM delivered extremely good performance, on 72 hr forecasts, with average errors below 6%. Emerging opportunities for integration come from advances in satellite-based and drone-assisted collection methods, in conjunction with IoT-based sensors, but there remain operational challenges to overcome, like the availability of geospatially-consistent datasets and scaling limitations. Explainable AI will be important for operational acceptance in helping bridge the gap between complexity of AI models and human understanding.

Table -1: SUMMARY OF REVIEWED FLOOD FORECASTING AND DETECTION MODELS

TITLE	YEAR	JOURNAL	METHODOLOGY/ ALGORITHM	GAPS/FINDINGS
Challenges and opportunities of AI for flood forecasting	2025	Springer	Random Forest, XGBoost, LSTM/RNN, CNNs for remote-sensed input, ensemble/hybrid methods	Heterogeneous inputs (gauge, radar/satellite, hydrologic states) are hard to fuse consistently; operationalization lags
Current status and challenges of AI in flood forecasting	2024	Frontiers	Classical ML (RF, XGBoost), deep models (LSTM, Bi-LSTM), and physics-informed hybrids	Lack of standardized data schemas; differing spatial/temporal resolutions hinder fusion
Skillful Prediction of Indian Monsoon Intraseasonal Precipitation Using ML	2024	Journal of Information System and Technology	Deep learning (LSTM, CNN-LSTM), sometimes gradient-boosted trees for baseline	Longer-lead temporal patterns (15+ days) encoded via ML; feature design around intraseasonal oscillations
Evolution of Data-Driven Flood Forecasting: 2019–2024	2025	IEEE	RF, XGBoost, LSTM, GNNs, hybrid process-ML	Weaknesses in evaluation design and temporal features across studies

Optimal threshold of issuing flash-flood warnings without uncertainty	2025	Springer	Statistical thresholding; sometimes logistic regression or probabilistic classifiers	Choosing alert thresholds under asymmetric costs; recall–precision trade-offs
Spatially transferable LSTM-based probabilistic flood-inundation forecasts	2025	PLOS ONE	LSTM with probabilistic output (e.g., MC Dropout, quantile loss), sometimes ensemble LSTMs	Probabilistic evaluation and calibration are underused in ops
Deep learning-based probabilistic flash-flood inundation forecasts	2024	Frontiers	Deep nets with probabilistic heads (e.g., Mixture Density Networks, quantile nets, or ensemble CNN/LSTM)	Event-level probability and decision thresholds for flash floods
Quick and large-scale spatiotemporal flood inundation forecasting	2023	EGU / Copernicus	Reduced-order deep surrogates (CNNs / U-Net variants), surrogate hydrodynamic models, sometimes encoder–decoder LSTM for time	Scaling fast city-level inundation from regional drivers
Flood Forecasting Model Using Federated Learning	2025	International Journal of Research Publication and Reviews	Local FFNNs at 18 stations aggregated via FL; gives 5-day alerts with privacy preserved	High communication cost; heterogeneous data hurts generalization
Prediction-to-Map framework for high-resolution river flows/inundation	2022	MDPI	Time-series forecast (LSTM/XGBoost) + spatial mapper (CNN or hydraulic routing surrogate)	Converting time-series predictions to maps at useful resolution
Global multi-basin flood risk under climate drivers (India focus within)	2024	EGU / Copernicus	Ensembles of ML regressors/classifiers (RF/XGBoost), sometimes statistical downscaling + ML	Basin-scale risk vs. city-scale decisions; confidence estimation
Flood susceptibility mapping of urban flood risk: Autoencoder MLP vs Logistic Regression	2024	Springer	Autoencoder compresses flood conditioning variables → latent features. LR compared against AE-MLP for susceptibility mapping.	Existing flood susceptibility mapping approaches struggle with high-dimensional data and correlated variables
Multi-Day Extreme Precipitation Caused Major Floods in India During 2024	2025	Frontiers	Event analysis; may use statistical attribution and ML diagnostics (LSTM / random forest) for precursors	Need for multi-day warning capability in Indian monsoon context

A Rapid Prediction Method for Key Information of the Urban Flood Control	2022	MDPI	Lightweight DNNs, gradient-boosted trees, or statistical regressors optimized for speed	Real-time prediction for operational decision points in cities
Machine Learning for Flood Resiliency—Current Status and Pathway Forward	2024	Springer Nature	RF, XGBoost, LSTM, CNN, GNN, hybrid physics-ML	Bridging research models to FEWS operations; data-scarce region constraints
Deep Learning Ensemble for Flood Probability Analysis (Nile basin)	2025	PLOS ONE	Ensemble of DNNs, CNN-LSTM, RF/XGBoost stacked ensembles	Using limited RS factors (rainfall/runoff/temp) with ensembles; uncertainty handling
Flood Forecasting Using Hybrid LSTM and GRU Models with Lag Time Preprocessing	2023	IEEE	Proposed CNN-LSTM hybrid for rainfall–runoff modeling; outperformed standalone CNN and LSTM	Needs larger datasets; weak generalization across basins; lacks operational testing
Multi-step Ahead Water Level Forecasting Using DNNs	2025	EGU / Copernicus	DNNs (Multi-step LSTM, Seq2Seq, or TCNs)	Early warning at multiple horizons; stability vs. lead time
Evaluating flood dynamics and effects in Nagpur using remote sensing & GIS	2024	Springer Nature	Remote sensing classification / change detection models (random forest, U-Net segmentation for water masks)	Urban growth + drainage → local vulnerability; need for ward-level mapping
Diffusion Models Improve Extreme Flood Prediction in ML Hydrology	2025	IEEE	Diffusion generative models adapted to time-series extremes; compared to LSTMs and ensembles	Tails/rare events poorly captured by standard DL
A Deep Learning Framework for Flash-Flood-Runoff Prediction	2025	IEEE	CNN/LSTM hybrids, Dense nets; sometimes U-Net for spatial run-off coupling	Integration with real-time monitoring left as future work
Water Flow Forecasting Based on Bi-LSTM with Temporal Weighting	2024	EGU / Copernicus	Bi-LSTM with attention/temporal weighting mechanism	Not all timesteps contribute equally; need temporal attention/weighting
Machine-Learning Flood Risk in Urban Watershed (XGBoost focus)	2025	Springer Nature	XGBoost / Random Forest / logistic regression for susceptibility mapping	Operational variable importance and city-scale features

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3. METHODOLOGY

A. Inclusion Criteria and Scope

The discussion focuses on evidence from a review of more than 22 recent scholarly articles, from years 2024-2025, on flood prediction, forecasting, vulnerability assessment and mitigation. The articles reviewed were included due to their significant contributions to

• Advancements in data-driven methods: Including Graph Neural Networks (GNNs), Diffusion Models (Generative AI) or improvements in sequence models (LSTM, GRU, AT-BiLSTM [22], LSTNet, DNNE),

• Hybrid Modelling: Combine Machine Learning (ML) with physics-based models (HEC-RAS, MIKE+, ParFlow-CLM, Neural ODEs [21]) or dynamic climate indicators (CIO mode, extreme return periods),

• Operational Relevance: Research to improve real-time capabilities and addressing data uncertainty (Data Drift), and probabilistic forecasting and converting a prediction to a real-world mitigative strategy (Digital Twins, urban planning).

B. Data Extraction and Synthesis

Articles were selected and examined to obtain comparative data across the following dimensions or characteristics of the articles.

1. Modelling Approach: Fully data-driven (ML/DL), fully physical/hydrodynamic, hybrid (i.e., ML combined with physics-based models, data assimilation, or Generative AI),

2. Model Algorithm: Determined all main ML/DL models (i.e., XGBoost, Random Forest, Logistic regression [23], LSTM, GNN, LSTNet, DRUM, EnKF).

3. Inputs/Features: All key predictive variables used (i.e., weather data, hydrological states, soil moisture, Shannon, etc.)

4. COMPARATIVE ANALYSIS

The reviewed literature clearly indicates a methodological shift away from using either a singular algorithm or simulations based only on physics, and towards a multi-faceted hybrid framework that captures the strengths of different models and datasets. This methodological transition is driven by the growing need for faster, more robust and probabilistically-sound forecasts of extreme events.

A. The Shift to Hybrid Architectures and Computational Efficiency

It should be noted that hybrid modeling is highly prevalent in all phases of prediction. Hybrid modeling solves the issue of the considerable high-cost computational nature of physics-based models, or the poor fidelity of basic statistical methods.

• Ultra-Fast Surrogates and XGBoost Dominance: Complex hydrodynamic models (e.g., MIKE+, HEC-RAS) are now routinely utilized for the sole purpose of generating data that can be used to train ultra-fast machine learning surrogates [7, 8, 14]. For example, XGBoost [14] is a solid option to achieve this task and can turn a slow MIKE+ simulation (21,600s) into a prediction under 0.2s [14]. Similarly, LSTNet [18] are even preferred in architectures due to their unique hybrid architecture (CNN + RNN/skip-RNN) and exhibit excellent operational durability from observation to prediction when large Data Drift are measured in the sensor time series.

• Enhanced Spatio-Temporal Networks: Deep Learning architectures place a premium on computational efficiency and memory usage. The STA-GRU (Spatio-temporal Attention Gated Recurrent Unit) [17] represents an architectural improvement, compared with STA-LSTM [17], and can produce similar prediction results with considerably faster training and deployment. Similarly, more advanced sequence models such as AT-BiLSTM [22] are now utilizing bidirectional temporal processing to improve the capability of long-range dependencies through the synchronization of elements both forwards.

B. Generative AI and Rigorous Probabilistic Forecasting

It is important to mention that hybrid modeling is widely used throughout all phases of prediction. Hybrid modeling resolves the issue of the substantial high-cost computation of physics-based models as well as the low-fidelity of basic statistical methods.

• Ultra-Fast Surrogates and XGBoost Predominance: Sophisticated hydrodynamic models (e.g., MIKE+, HEC-RAS) are often being utilized solely for data generation to build ultra-fast machine learning surrogates [7, 8, 14]. In particular, XGBoost [14] is a powerful contender for this and can take a slow MIKE + simulation (21,600s) and yield a prediction in less than 0.2s [14]. Providers for LSTNet [18] will experience the same benefits and are preferred in architecture due to their novel hybrid architecture (CNN + RNN/skip-RNN) while exhibiting excellent operational durability from observation to prediction, particularly when large Data Drift are noted in the sensor time series.

• Improved Spatio-Temporal Networks: Efficient computation and memory use are one of the notable price tags for deep learning architecture. Even though STA-GRU (Spatio-temporal Attention Gated Recurrent Unit) [17] is an architectural advance over STA-LSTM [17], it is capable of similar predictive performance, because it used considerably less time to train and deploy. Similarly, AT-Bi LSTM [22] is advancing sophisticated sequence models by applying bidirectional temporal processing to improve their competency.

C. Interpretable Drivers and Actionable Risk Assessment

The large feature space requires advanced tools to analyze drivers, which often means that there is a trade-off between how complex the model is and how easy it is to understand for policy.

• Drivers of Urbanization and Entropic Analysis: Potential dangers in cities are becoming more and more dependent on how people interact with each other. New frameworks, like Shannon's Entropy analysis [19], help us measure disorder and fast changes in Land Use/Land Cover (LULC). These changes are linked to the development of land as water bodies and fallowed areas become more prone to flooding. This is another way of stressing how important it is to include planning in susceptibility mapping.

• Foremost Features in Susceptibility: Simpler models often yield better interpretability and accuracy in flood susceptibility mapping. By way of example, utilizing Logistic Regression [23] for the Briar Creek watershed yielded almost perfect accuracy and perfect precision, and greatly reduced costly false warnings, when it relied on the distinct linear correlation of key physical drivers; The literature consistently identifies elevation and distance to river (DTR) as the most significant drivers across all models [23, 8].

• Digital Twins for Policy Action: The creation of Digital Twin frameworks [12] is a crucial last link. With the help of these tools, users can visually reproduce intricate GNN predictions and test and assess mitigation strategies (such as the use of barriers) over tenants' actions or engagement in real time.

5. CONCLUSION

5.1. Summary of Findings

The coherent summary gives an idea of the current flood prediction environment, where hybrid, data-driven approaches are being hurriedly implemented to address practical operational challenges. Almost unanimously, the general takeaway is that the systemic need to address the issues cannot be met by purely statistical approaches or by strictly physical models. The most successful modern approach combines the effectiveness of generative artificial intelligence (AI) or machine learning statistics techniques with physical principles or principles that frequently use physical modeling, and most of the time, results in actionable trails.

1. Core Technological Stack: The value of the recently introduced Diffusion Models (DRUM) [20] for extreme probabilistic forecasting is the adaptability of spatio-temporal models (GNN [7,12], AT-Bi LSTM [22]). Learning constraints and limitations in discrete time are being overcome by neural ODEs [21] for continuous time physics modelling.

2. Drivers and Visualization: Because forecasting is contextual, it produces complex features like atmospheric drivers (IVT), lag time preprocessing, and objective metrics to measure the physical impact of urbanization (Shannon's Entropy [19]). In the end, Digital Twins serves as the official end-user interface for all intricate, accurate forecasts in order to visually represent and formally implement a mitigation strategy.

3. Probabilistic Rigor: The discussion has shifted from deterministic errors (RMSE) to thorough, holistic uncertainty quantification and adopting less deterministic, distribution-free metrics (CRPS) that take performance maturity to the quantification of uncertainty, now moving to quantified risk (fbeta or FORM)

5.2. Future Research Directions and Gaps

There are several gaps in this synthesis, as well as some potentially beneficial future directions:

1. Investigating DRUM [20] (Diffusion Models) is warranted to accommodate multiple contextual inputs (e.g., LULC maps, evolving topography, sensor data), and thus more sophisticated distribution-free probabilistic predictions on top of the basic meteorological input.

2. Research needs to be directed to validate flood mitigation strategies developed through Digital Twins [12] through comparing them to flood responses in the "real world". More importantly, there was an emphasis on the availability of robust feedback loops to connect real-time sensor data back to the modelled ecosystem for continual calibration.

3. The benefits of Lag Time Preprocessing [17] should be automated, and implemented across entire hydrometric networks, not just implemented on an ad-hoc basis. This could include intra-GNN frameworks.

4. Future modelling must fully account for the social aspects [5] of urban infrastructure (as discussed regarding failure conditions [14]) in addition to hazard prediction that would provide true, risk based socio-ecological resilience assessments [15].

5. The use of Transfer Learning in hydrologic models is still infrequently reported, despite it being discussed as a significant gap [15]. More explicitly targeted research is required to develop foundational models that may be easily adaptable in low data contexts, and in often ungauged areas.

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