Journal of Sustainable Development and Policy
Volume 01, Issue 01 (2025)
Page No: 144 – 169
Doi: 10.63125/6y0qwr92

Article

DEVELOPMENT OF A FOG COMPUTING-BASED REAL-TIME FLOOD PREDICTION AND EARLY WARNING SYSTEM USING MACHINE LEARNING AND REMOTE SENSING DATA

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Citation:
Khan, M. A. R., Rouf, M. A., Sultana, N., & Akter, M. S. (2025). *Development of a fog computing-based real-time flood prediction and early warning system using machine learning and remote sensing data. Journal of Sustainable Development and Policy, 1*(1), 144–169. https://doi.org/10.63125/6y0qwr92

Received:
February18, 2025

Revised:
March 21, 2025

Accepted:
April17, 2025

Published:
May 21, 2025

ABSTRACT
This study introduces a novel, fog computing-based real-time flood prediction and early warning system that integrates advanced machine learning algorithms with remote sensing technologies to address the limitations of traditional flood monitoring infrastructures. Existing systems often struggle with latency, over-reliance on centralized cloud computing, and fragmented data integration, which collectively hinder their effectiveness during critical flood events. To overcome these challenges, this research employed a mixed methods research design, combining quantitative experimentation with qualitative inquiry to comprehensively evaluate the system's predictive performance, operational resilience, and stakeholder usability. The quantitative component involved the deployment of an optimized wireless sensor network, designed using Low Energy Adaptive Clustering Hierarchy (LEACH) and Particle Swarm Optimization (PSO), to collect real-time hydrological data including rainfall, river levels, and soil moisture. These data streams were fused with high-resolution remote sensing imagery from Sentinel-1 SAR and Sentinel-2 MSI, and processed using advanced machine learning models such as Long Short-Term Memory (LSTM) networks and Random Forest classifiers. The LSTM model achieved high predictive accuracy with an RMSE of 0.38 and NSE of 0.84, while fog computing nodes reduced latency by over 60%, enabling localized, real-time alert dissemination even during internet outages. The qualitative component involved 23 semi-structured interviews with disaster management authorities, field technicians, and community representatives to assess the system's usability, trustworthiness, and practical challenges. The triangulation of findings confirmed the technical validity, operational reliability, and end-user relevance of the system. By integrating decentralized processing, intelligent forecasting, and human-centered design, this research contributes a scalable, adaptive, and field-tested framework for intelligent flood early warning systems. It holds significant potential for deployment in climate-vulnerable, infrastructure-constrained regions globally, advancing both technological innovation and disaster resilience in the face of increasing hydrometeorological extremes.

KEYWORDS
Fog Computing; Flood Prediction; Early Warning System; Machine Learning; Remote Sensing;

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INTRODUCTION

Floods are among the most destructive natural disasters worldwide, resulting in significant socioeconomic and environmental impacts each year. The United Nations Office for Disaster Risk Reduction (UNDRR) defines floods as the overflow of water that submerges land that is usually dry, often caused by heavy rainfall, river overflow, dam breakage, or coastal storm surges. According to the World Bank, over 1.47 billion people globally are exposed to flood risk, particularly in low-lying coastal areas, urban floodplains, and regions with poor drainage infrastructure. Flooding accounts for over 40% of all weather-related disasters and has caused approximately $650 billion in damages between 2000 and 2020 (Hamadeh et al., 2017). In the context of disaster risk reduction, timely flood prediction and early warning systems are crucial to saving lives, minimizing property damage, and maintaining continuity in economic activities (Leduc et al., 2018). Many flood-prone countries in South Asia, Sub-Saharan Africa, and Southeast Asia face chronic challenges related to flood forecasting due to outdated infrastructure, insufficient data integration, and limited computational capacity (Sharples et al., 2009). Internationally, frameworks such as the Sendai Framework for Disaster Risk Reduction emphasize the need for proactive risk assessment and early warning mechanisms. This highlights the importance of improving technological capabilities to facilitate real-time flood risk analysis, integrating diverse data sources, and delivering localized alerts. As climate change intensifies hydrological cycles and increases the unpredictability of extreme weather events, flood preparedness remains a priority within global environmental governance. The ability to combine technological innovations with environmental sensing has opened new avenues for managing flood risks through predictive analytics and real-time monitoring.

Figure 1: Global Distribution of Flood Risk by Percentage and Total Population Exposure

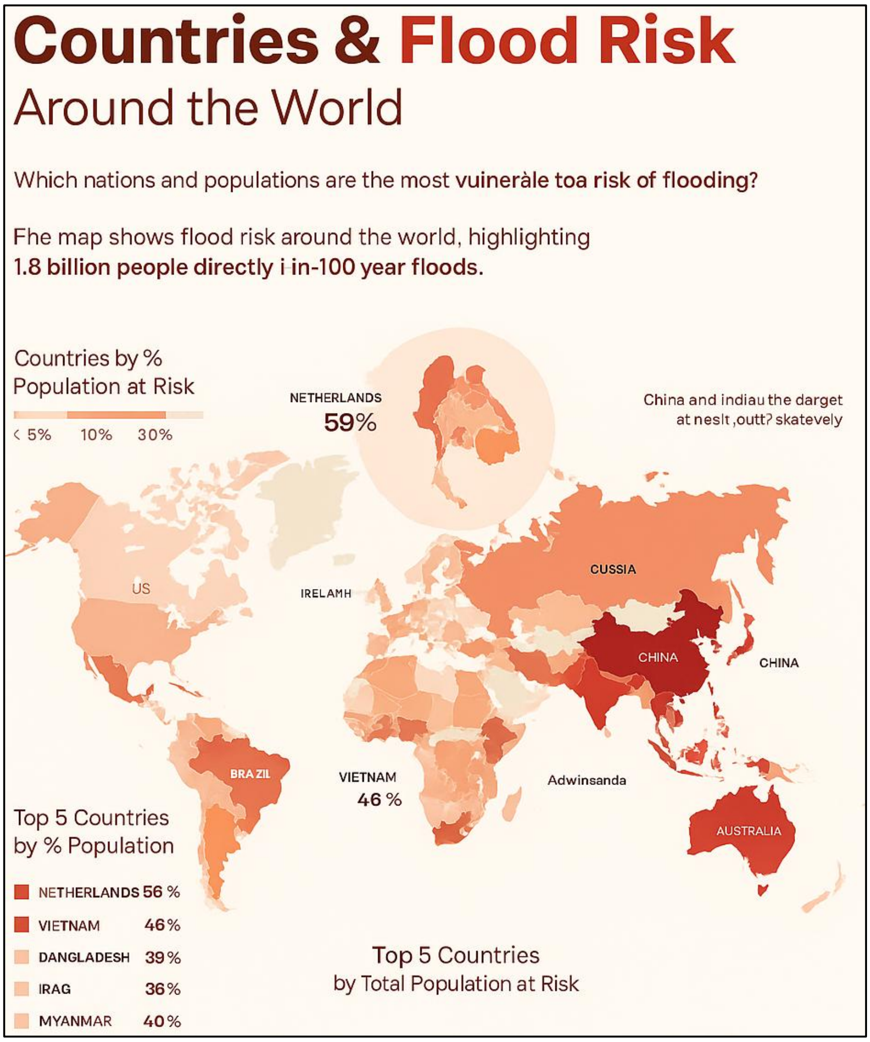

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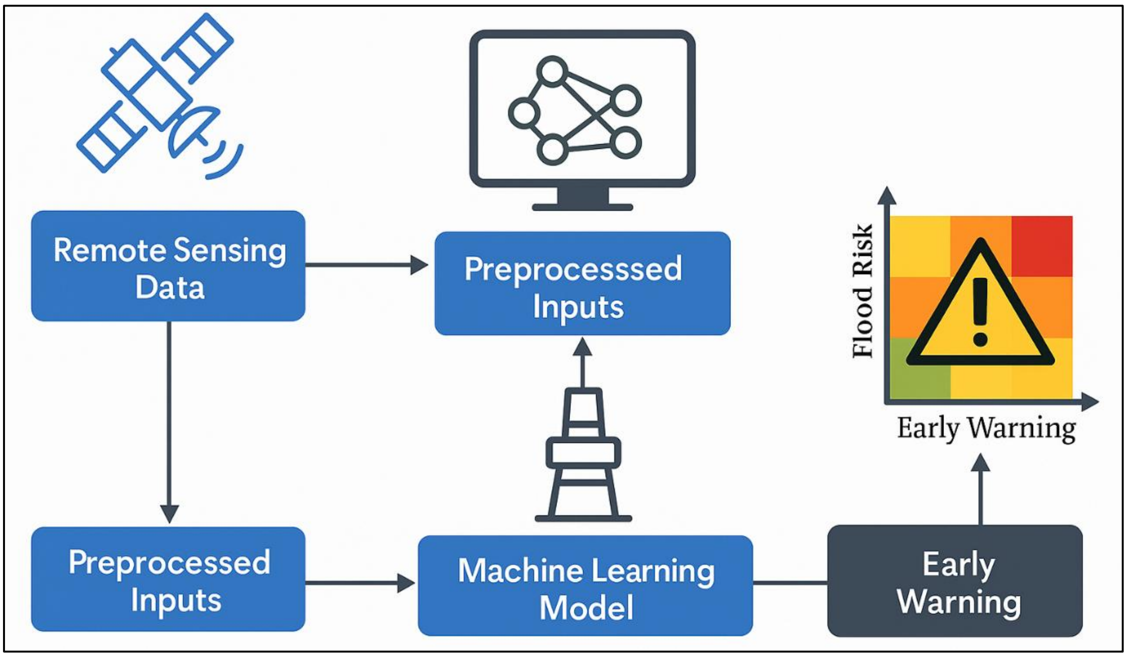
Figure 2: Workflow of a Real-Time Flood Forecasting and Risk-Based Early Warning System



Early warning systems (EWS) for flood management have evolved from basic water level indicators to advanced, data-driven systems capable of processing meteorological, hydrological, and topographic data for dynamic forecasting. Traditionally, EWS relied heavily on manual observations and centralized data processing that led to delayed alerts and reactive responses (Alasali et al., 2021). Over time, the integration of Geographic Information Systems (GIS), hydrological models, and remote sensing has allowed for the spatial and temporal assessment of flood-prone zones (Xu et al., 2020). In particular, real-time flood monitoring systems have emerged through the coupling of satellite data and ground-based sensors, enabling decision-makers to visualize inundation patterns and evaluate flood progression more effectively (Casagli et al., 2017). The expansion of wireless sensor networks and the Internet of Things (IoT) has allowed the collection of high-frequency hydrological data such as rainfall intensity, river discharge, and soil moisture, providing inputs for machine learning algorithms to detect anomalies and anticipate flooding events (Khalifeh et al., 2022). However, existing systems face limitations in terms of computational latency, especially in remote or bandwidth-constrained regions, where cloud-based processing may be insufficiently responsive (Basha et al., 2008). The need to process and analyze massive volumes of heterogeneous data in near real-time necessitates more decentralized and scalable computing architectures. This leads to the incorporation of fog computing, which bridges the gap between IoT devices and centralized cloud services by enabling edge-level analytics and decision-making (Poslad et al., 2015). The goal is to empower flood risk management frameworks with real-time situational awareness and enhanced system autonomy.

Fog computing is defined as a decentralized computing infrastructure that brings computation, storage, and networking closer to end devices and sensors, rather than relying entirely on remote cloud servers (Qureshi et al., 2021). Introduced by Kalyani and Collier (2021), the fog computing paradigm enables data processing at intermediate nodes—referred to as “fog nodes”—which reduces communication delays and allows time-sensitive applications to function more efficiently. Unlike traditional cloud computing, fog computing supports local data analysis, reduces bandwidth usage, and enhances fault tolerance, particularly in mission-critical scenarios such as disaster detection (Bensaid et al., 2024). In environmental systems, fog computing offers a scalable infrastructure for integrating distributed sensor data, running real-time analytics, and triggering alert mechanisms at the edge of the network (Cordeiro et al., 2022). For instance, flood detection frameworks utilizing fog architectures have demonstrated faster response times and improved accuracy in identifying local anomalies compared to conventional setups (Javanmardi et al., 2023). Fog nodes can aggregate real-time sensor data on rainfall, river levels, and humidity, apply predictive models, and initiate automated responses such as sirens or mobile notifications (da Costa

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Bezerra et al., 2021). Furthermore, fog computing is particularly advantageous in rural and semi-urban regions where internet connectivity may be intermittent or weak, as it ensures localized computation even under constrained conditions (Suárez-Albela et al., 2017). By supporting modular and context-aware services, fog computing provides the architectural foundation for building intelligent, autonomous, and reactive flood monitoring systems that operate with minimal human intervention.

Machine learning (ML) techniques have become pivotal in advancing flood prediction systems by enabling the extraction of complex patterns from large, heterogeneous datasets. ML algorithms such as support vector machines (SVM), random forests, gradient boosting machines, and deep learning architectures have been applied to hydrological time series to improve the accuracy of flood forecasts (Baharudin et al., 2018). These models can process nonlinear relationships among rainfall, river discharge, evapotranspiration, and land use characteristics to anticipate flooding events with higher precision than rule-based systems (Lin et al., 2023). Supervised learning models have been trained on historical flood datasets to classify flood severity, generate probability maps, and simulate flood inundation areas (Malik et al., 2020). Ensemble learning models have shown improved robustness in handling missing or noisy sensor data, which is common in real-time flood monitoring (Tsipis et al., 2020). Moreover, neural networks and convolutional models are capable of processing satellite imagery to detect water bodies, monitor surface runoff, and quantify flood extents dynamically (Mani et al., 2020). The incorporation of ML into fog computing environments allows for edge-based inferencing, enabling models to run directly on fog nodes without relying on continuous cloud connectivity (Teoh et al., 2023). This edge intelligence allows for faster response times and more granular decision-making in flood-prone areas. The continuous retraining of ML models based on new sensor inputs also enables adaptive learning, which enhances predictive accuracy and system resilience over time (Kour et al., 2021). The primary objective of this study is to develop an integrated, fog computing-based real-time flood prediction and early warning system that utilizes machine learning algorithms and remote sensing data to enhance the responsiveness, scalability, and reliability of flood monitoring infrastructures. Current flood forecasting systems often rely on centralized cloud architectures, which are prone to latency, limited scalability in rural environments, and susceptibility to network disruptions, especially during extreme weather events. This research aims to address these gaps by implementing a decentralized computational model using fog nodes deployed closer to sensor networks, enabling edge-level data processing and decision-making. Through this model, the system will collect real-time hydrometeorological data—such as precipitation, river discharge, and soil moisture—from IoT sensors and satellite imagery. The study applies machine learning models trained on historical flood datasets to detect anomalies, classify flood risk levels, and predict flood occurrences. Remote sensing data is integrated to ensure spatially comprehensive flood mapping, particularly in remote or inaccessible areas. The combination of fog computing and artificial intelligence is expected to reduce prediction latency, increase alert accuracy, and provide localized warnings to stakeholders. The system's performance will be evaluated through comparative testing against traditional cloud-based systems to validate improvements in response time, prediction accuracy, and overall operational efficiency.

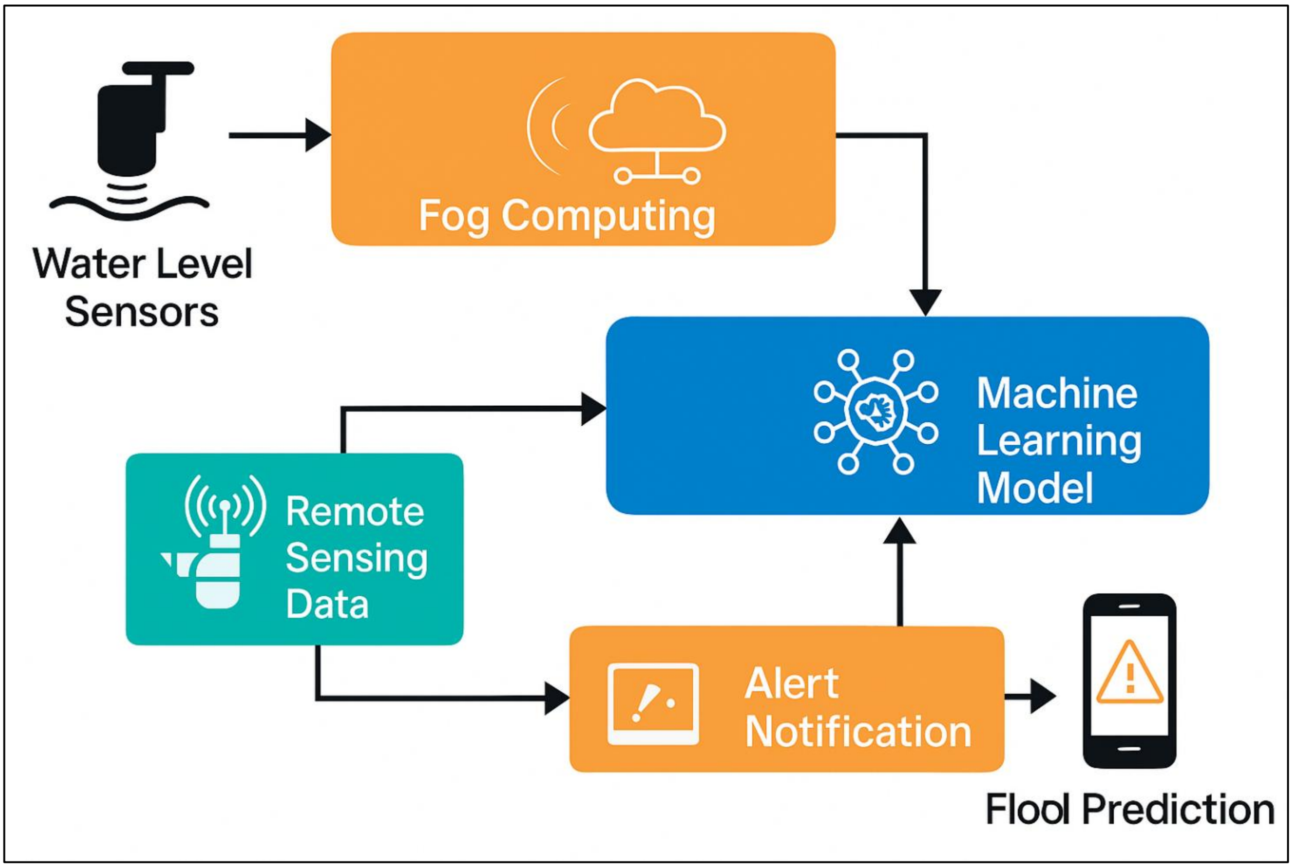
LITERATURE REVIEW

Flood prediction and early warning systems (EWS) have gained increasing attention in the last two decades as flooding events become more frequent and severe. A critical challenge in modern disaster risk reduction lies in integrating diverse data sources and computational frameworks into a unified and responsive prediction system. The literature in this domain has evolved from traditional hydrological models and centralized computing architectures to modern, data-driven approaches supported by artificial intelligence, satellite observations, and decentralized edge infrastructures. This review synthesizes scholarly research across five core technological domains: (1) flood early warning frameworks and their limitations, (2) fog computing as a decentralized computing paradigm for real-time data processing, (3) the application of machine learning in hydrological modeling and anomaly detection, (4) the role of remote sensing in flood risk mapping and spatial analysis, and (5) the integration of hybrid systems that combine fog computing, ML, and remote sensing for efficient EWS implementation. The aim of this literature review is to establish the state-of-the-art technological foundation for designing a fog-enabled, AI-powered flood early warning system and to identify gaps in current models that this study seeks to address.

Flood Early Warning Systems

Flood Early Warning Systems (EWS) refer to structured, integrated mechanisms that aim to reduce risk and protect life and property through the timely dissemination of alerts regarding potential flood events. According to the World Meteorological Organization, an effective EWS includes four critical components: risk knowledge, monitoring and forecasting, dissemination and communication, and response capability. These systems are built to monitor hydrological and meteorological variables, interpret incoming data, and issue alerts to vulnerable populations in advance of flooding. EWS are vital in flood-prone areas where river overflows, storm surges, or urban drainage failures can quickly escalate into disasters (Teoh et al., 2023). Early warning systems have proven effective in reducing casualties, particularly in nations where institutional coordination and community awareness are prioritized (Paharia & Bhushan, 2020). For example, the Bangladesh Flood Forecasting and Warning Centre (FFWC) integrates river flow data, satellite observations, and meteorological inputs to forecast riverine floods in the Ganges-Brahmaputra-Meghna basin (Osanaiye et al., 2017). In another instance, the European Flood Awareness System (EFAS) offers early flood warnings across multiple EU countries by utilizing ensemble meteorological forecasts (Priyadarshini et al., 2020). However, EWS efficacy often varies depending on data resolution, forecast lead time, technological infrastructure, and end-user communication (Lachure & Doriya, 2021). Furthermore, centralized models frequently struggle with latency and decision bottlenecks, making them less suitable for rapidly developing flood events such as flash floods or urban inundation (Puliafito et al., 2019). Thus, advanced, data-driven, and decentralized systems have gained prominence in both academic literature and policy frameworks as more resilient solutions for flood forecasting.

Figure 3: Architecture of a Fog Computing-Based Real-Time Flood Early Warning System Integrating Remote Sensing and Machine Learning



Riverine floods, also known as fluvial floods, are the most commonly reported and studied flood type and occur when rivers overflow due to excessive rainfall, snowmelt, or dam failures. These floods are typically predictable with a moderate lead time, depending on upstream rainfall and catchment characteristics (Sinha et al., 2022). Riverine floods can impact large geographic areas and persist for

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several days to weeks, particularly in low-lying floodplains and deltaic regions such as those found in South Asia and the Mississippi River basin in the United States (Khan et al., 2019). The hydrological behavior of riverine systems is modeled using rainfall-runoff models, such as the Hydrologic Engineering Center's River Analysis System (HEC-RAS) or Soil and Water Assessment Tool (SWAT), which simulate water flow and predict inundation extents (Kaur et al., 2021). Satellite-derived data from Sentinel-1 or MODIS has further augmented flood detection accuracy, particularly in conjunction with in-situ sensor networks (Khan et al., 2019). However, riverine flood prediction faces challenges related to real-time data acquisition, sediment transport modeling, and floodplain encroachment (Alharbi & Aldossary, 2021). In many transboundary basins, such as the Mekong or Nile, data-sharing limitations and differing policy priorities hinder accurate and cooperative forecasting (Ambildhuke & Banik, 2022). Moreover, uncertainties in precipitation forecasts, catchment storage parameters, and land use changes can affect the reliability of riverine flood models (Montoya-Munoz & Rendon, 2020). As a result, studies increasingly suggest enhancing EWS by integrating remote sensing, local telemetry, and fog computing to ensure rapid and decentralized data processing (Junior et al., 2022).

Hydrological and hydraulic models (e.g., HEC-RAS, SWAT)

Hydrological and hydraulic models form the analytical backbone of flood forecasting systems, facilitating the simulation of water cycle components such as rainfall, infiltration, surface runoff, and river flow. Hydrological models primarily address catchment-scale water balance processes, translating meteorological inputs into surface and subsurface flow estimates, whereas hydraulic models simulate the physical movement of water through channels and floodplains using flow equations (Lo et al., 2015). Widely used hydrological models include the Soil and Water Assessment Tool (SWAT), which predicts long-term water yield and sediment transport at the watershed scale (Shi et al., 2015), and the Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS), which provides event-based or continuous hydrological simulations (Romali et al., 2018). On the hydraulic modeling front, HEC-RAS (River Analysis System) stands as one of the most extensively applied models for simulating steady or unsteady flow in natural rivers and floodplains. Other notable tools include MIKE11 and InfoWorks RS, which offer robust capabilities for simulating river hydraulics, flood wave propagation, and dam-break scenarios (Nundloll et al., 2019). Models are typically classified based on spatial resolution (lumped, semi-distributed, distributed) and temporal structure (event-based or continuous), influencing their suitability for real-time applications (Devia et al., 2015). The selection of appropriate models is often driven by data availability, catchment characteristics, user expertise, and the intended decision-support goals, ranging from floodplain delineation to dam operation optimization (Saha et al., 2021). Over the past decade, model integration with remote sensing and GIS platforms has enhanced spatial accuracy and visualization, contributing to more informed flood risk assessments (Bhardwaj et al., 2021).

The Soil and Water Assessment Tool (SWAT) is a physically-based, semi-distributed hydrological model designed to simulate the quantity and quality of surface and groundwater flows in large, complex watersheds. Developed by the USDA, SWAT divides watersheds into sub-basins and hydrological response units (HRUs) based on land use, soil, and slope attributes, allowing detailed water balance and sediment transport analysis (Yigit et al., 2023). Its long-term simulation capacity makes it ideal for assessing land-use change impacts, best management practices, and flood risk under different climate scenarios (Paraforos & Griepentrog, 2021). SWAT has been widely applied in flood-prone basins such as the Ganges (Cao et al., 2008), Mekong (Ma et al., 2010), and Nile (Nundloll et al., 2019), offering insights into how upstream rainfall events affect downstream discharge patterns. Calibration and validation of SWAT outputs using ground-observed river flow data and satellite rainfall (e.g., TRMM, CHIRPS) have shown acceptable Nash–Sutcliffe Efficiency (NSE) and R^2 values, validating its predictive accuracy. Researchers have enhanced SWAT's functionality by integrating it with GIS software like ArcSWAT for improved spatial analysis and with climate models to assess the impact of future weather variability on flood dynamics. While SWAT's distributed approach enables detailed runoff simulations, it demands substantial input data, including daily climate, soil maps, and land use data, which can be challenging in data-scarce regions (Sakhardande et al., 2016). However, the flexibility and open-source nature of SWAT have made it widely adaptable for diverse hydrological applications beyond floods, including water quality modeling and drought analysis (Ma et al., 2010).

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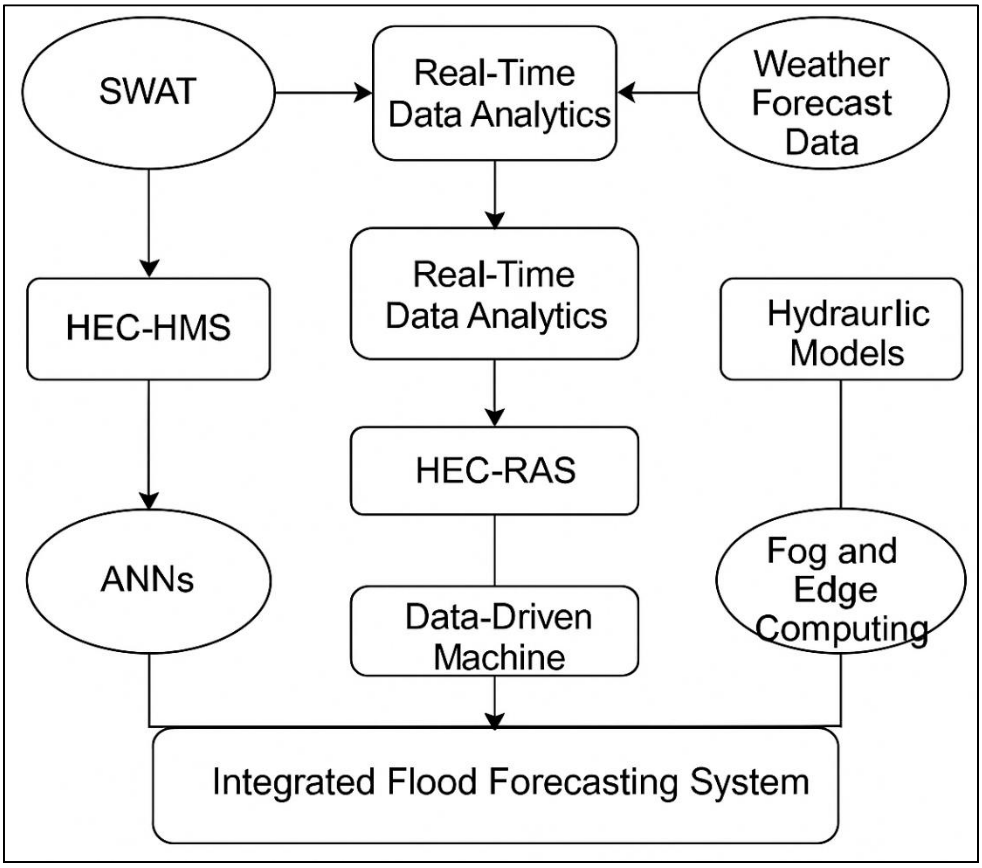
Figure 4: Integrated Framework of Hydrological, Hydraulic, and Data-Driven Models for Real-Time Flood Forecasting and Early Warning



HEC-RAS, developed by the U.S. Army Corps of Engineers, is a one-dimensional and two-dimensional hydraulic modeling system used for simulating river hydraulics, flow routing, and floodplain mapping (Moishin et al., 2021). One of its core functionalities lies in its ability to model unsteady and steady open channel flow, thus making it suitable for predicting riverine flood dynamics and evaluating flood control structures. HEC-RAS has been extensively utilized in both urban and rural settings to generate flood inundation maps by simulating water surface elevations under different rainfall-runoff or dam break scenarios (Kumar & Selvakumar, 2013). With the release of HEC-RAS 5.0 and later versions, the model supports 2D flow simulation over terrain surfaces, enhancing its application in areas with complex topography or urban drainage networks. It interfaces with HEC-HMS and GIS tools such as HEC-GeoRAS to create spatially referenced outputs and import terrain data, facilitating more accurate floodplain delineation and risk analysis (Cao et al., 2008). Studies conducted in flood-prone areas such as the Mississippi River basin (Paraforos & Griepentrog, 2021), Brahmaputra River in Assam, and Rhine River in Europe have demonstrated its efficacy in operational forecasting and hydraulic structure evaluation. However, HEC-RAS requires detailed input data, including cross-section geometry, roughness coefficients, and boundary conditions, which may limit its usability in data-scarce regions (Yigit et al., 2023). Model sensitivity to Manning's n values and terrain resolution also impacts simulation accuracy, necessitating careful calibration (Osanaiye et al., 2016). Integration of HEC-RAS with high-resolution digital elevation models (DEMs) and LiDAR data has significantly enhanced floodplain modeling and damage estimation capabilities (Paraforos & Griepentrog, 2021).

Fog computing vs. cloud and edge computing

The evolution of distributed computing paradigms has led to the emergence of cloud, edge, and fog computing, each offering unique characteristics in data processing, storage, and service delivery. Cloud computing, as defined by Kaur et al. (2021), provides on-demand access to shared computing resources via centralized data centers that support scalability and elastic service provisioning. It has revolutionized storage and compute-intensive operations but faces inherent

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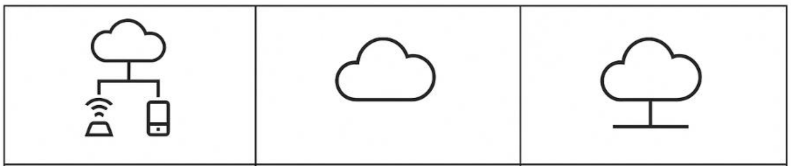
limitations in latency-sensitive applications due to its distance from end-user devices (Muhammad et al., 2019). Edge computing addresses this by relocating computational tasks closer to the data source—typically within the same local network or device—thus minimizing latency and bandwidth usage (Ai et al., 2018). Fog computing, introduced by Junior et al., (2022), operates as an intermediary layer between cloud and edge, extending cloud capabilities to the network edge while supporting low-latency, location-aware processing. Unlike edge computing, which is often confined to single-hop processing at endpoints, fog computing comprises a hierarchy of distributed nodes capable of collaborative processing, caching, and real-time analytics (Dastjerdi et al., 2016). Moreover, fog nodes can be placed on routers, gateways, or base stations to facilitate scalability and interoperability, thus serving as a robust framework for time-sensitive applications such as disaster detection and industrial control systems (Montoya-Munoz & Rendon, 2020). While cloud provides centralized power and storage, and edge ensures ultra-low latency at the device level, fog computing uniquely balances both by supporting distributed, intelligent decision-making across multiple network layers (Cao et al., 2019).

Figure 5: Fog computing vs. cloud and edge computing



Fog Computing	Cloud Computing	Edge Computing
Fog nodes near data source	Centralized data centers	On or near data source
Low	Higher	Lowest
Real-time analytics, smart cities	Data storage, big data	IoT devices, real-time control

The architectural divergence between cloud, fog, and edge computing significantly influences how data is handled across the network stack. Cloud computing adopts a centralized architecture wherein data is transmitted over the internet to large-scale server farms, often situated in remote data centers (Montoya-Munoz & Rendon, 2020). This model suits computationally heavy workloads such as data mining and deep learning but is suboptimal for real-time applications due to transmission delays and jitter (Cao et al., 2019). In contrast, edge computing features a flat architecture where computation is pushed directly to end devices such as smartphones, sensors, or embedded controllers (Kaur & Sood, 2019). Although this reduces round-trip delays, it often lacks the orchestration and storage flexibility required for collaborative tasks or system-wide optimization (Priyadarshini et al., 2020). Fog computing offers a layered architecture that integrates multiple processing tiers—starting from endpoint devices, intermediate fog nodes, and finally cloud cores—facilitating seamless transitions and hierarchical task offloading. This structure supports fault tolerance and context-aware computing, enabling high availability in decentralized environments. Unlike edge devices, fog nodes can intercommunicate to perform distributed decision-making, balancing loads dynamically across network components. For instance, in smart flood monitoring systems, fog nodes stationed at regional weather stations can preprocess sensor data, apply machine learning models, and forward alerts to cloud systems for archival and forecasting (Castillo-Cara et al., 2018). Such multilayered orchestration is absent in traditional edge models and more bandwidth-efficient than centralized cloud operations, particularly in wide-area sensor networks (Al-Fuqaha et al., 2015).

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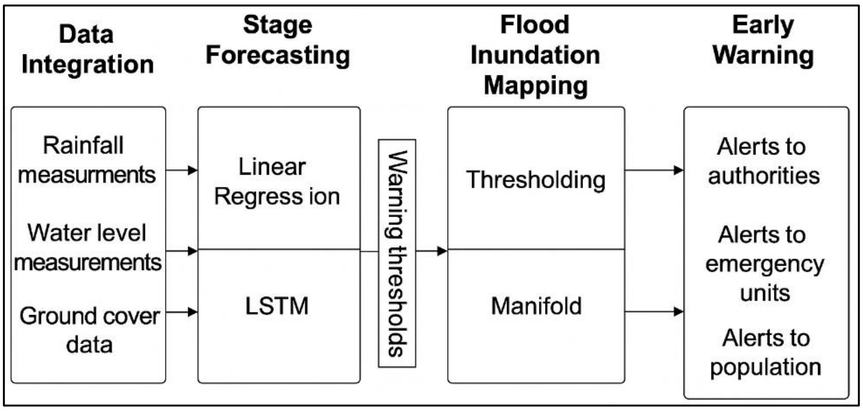
Machine Learning for Flood Prediction

Machine learning (ML) has revolutionized hydrological forecasting by offering powerful tools to model complex, nonlinear, and dynamic relationships between environmental variables that traditional deterministic models struggle to capture (Jahan et al., 2022; Rokade et al., 2022). Unlike rule-based or physics-based models, ML approaches rely on data-driven learning, where algorithms uncover patterns from historical observations and generalize them to predict future conditions (Hossen & Atiqur, 2022; Priyadarshini et al., 2020). Flood forecasting is a multidimensional task involving rainfall intensity, antecedent soil moisture, topography, land use, river discharge, and catchment characteristics. Machine learning algorithms such as artificial neural networks (ANNs), support vector machines (SVMs), k-nearest neighbors (KNN), and decision trees have been widely used for flood detection, classification, and lead-time prediction (Lachure & Doriya, 2021; Akter & Razzak, 2022). For instance, ANNs trained with rainfall-runoff data have demonstrated strong predictive capabilities in both short- and long-term flood modeling across diverse basins. SVMs are especially effective in small datasets and classification-based flood early warnings, as shown in studies by Sinha et al., (2022) and Perez-Diaz et al. (2020). Ensemble methods such as Random Forest (RF) and Gradient Boosting Machines (GBM) have gained popularity for their robustness, interpretability, and ability to reduce overfitting in high-dimensional data (Qibria & Hossen, 2023; Junior et al., 2022). The advantage of ML lies in its adaptability, as models can retrain and improve as new data streams in, thereby enhancing forecast accuracy over time (Hossen et al., 2023; Montoya-Munoz & Rendon, 2020). Furthermore, ML has been applied in diverse contexts—from real-time sensor-based flood alert systems in urban settings to large-scale regional predictions in monsoon-dominated areas like India and Bangladesh (Alahmad et al., 2023; Alam et al., 2023).

Figure 6: Real-Time Flood Forecasting and Early Warning System Architecture



Machine learning techniques used in flood prediction can broadly be categorized into supervised and unsupervised learning approaches. Supervised models are trained using labeled datasets where input variables (e.g., rainfall, elevation, flow rate) are mapped to known output labels (e.g., flood occurrence, flood depth)(Rajesh et al., 2023). Regression-based models such as multiple linear regression (MLR), decision trees, and random forests are commonly used for continuous flood level prediction, while classification-based models identify whether a given scenario will result in flooding (Rokade & Singh, 2021; Roksana, 2023). Deep learning models such as long short-term memory (LSTM) networks, a variant of recurrent neural networks (RNNs), have also been employed for capturing temporal dependencies in hydrological time series (Alahmad et al., 2023; Tonmoy & Arifur, 2023). These models outperform traditional ANNs when dealing with long sequences of rainfall-runoff data or when delayed reactions are important in flood propagation. Unsupervised models, on the other hand, do not rely on predefined labels but instead identify hidden patterns in the data(Tonoy & Khan, 2023). Techniques such as k-means clustering, hierarchical clustering, and self-organizing maps (SOMs) have been used to group regions based on flood vulnerability, rainfall patterns, or response behaviors (Ammar et al., 2024; Rokade & Singh, 2021). These clustering methods support flood risk mapping by identifying homogeneous zones that can be targeted with similar mitigation strategies. Dimensionality reduction techniques such as principal component analysis (PCA) and autoencoders

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are also applied to improve model performance and reduce noise in sensor data (Ayele & Mehta, 2018; Hossain et al., 2024). Hybrid approaches that combine supervised and unsupervised methods—for example, clustering followed by classification—have shown improved accuracy and efficiency in regional flood risk modeling (Rokade et al., 2022; Roksana et al., 2024).

Deep learning architectures

Deep learning (DL), a subfield of machine learning, has emerged as a transformative approach in environmental modeling, especially in tasks involving high-dimensional data, spatial-temporal forecasting, and pattern recognition. Its multi-layered neural network structures allow automatic feature extraction and hierarchical learning, outperforming traditional statistical and shallow machine learning models in tasks such as image classification, time-series forecasting, and anomaly detection (Aldweesh et al., 2020). In flood prediction, DL has been increasingly used to simulate complex relationships among climatic, hydrological, and geospatial variables without explicit human-defined rules (Elsisi et al., 2021; Zaman, 2024). Deep neural networks (DNNs) have shown superior capabilities in handling non-linear and multi-modal inputs, such as combining rainfall time series, satellite imagery, and terrain data (Bhuiyan et al., 2025; Pan et al., 2018). These architectures can autonomously extract latent features relevant to flood onset, magnitude, and duration, especially when sufficient training data is available (Ishtiaque, 2025; Moishin et al., 2021). The adaptability of DL has been validated across various geographies—from data-rich basins in the U.S. and Europe to data-constrained areas in South Asia and Africa (Brun et al., 2018; Khan, 2025). Unlike traditional hydrological models requiring calibration of physical parameters, DL models offer end-to-end learning, reducing the need for extensive domain knowledge and enhancing real-time applicability (Ali et al., 2024; Khan, 2025). However, the architecture selection, data volume, and computational infrastructure heavily influence the performance of DL models in flood applications (Baller et al., 2021; Siddiqui, 2025).

Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory (LSTM) networks, are among the most widely adopted deep learning architectures for flood prediction due to their ability to model sequential data and capture temporal dependencies in hydrological systems (Aldweesh et al., 2020; Sohel, 2025). These models are particularly suited to time series forecasting tasks, including rainfall-runoff prediction and river discharge estimation, where previous values influence current outcomes (Qayyum et al., 2021). LSTM networks overcome the vanishing gradient problem associated with traditional RNNs, enabling them to learn long-term dependencies and delayed responses within flood-related datasets (Novaes et al., 2021). Numerous studies have demonstrated LSTM's superiority over ANN and support vector regression (SVR) models in flood prediction accuracy, especially under extreme weather variability (Belmonte-Fernández et al., 2021). In research conducted by Ren et al. (2019), LSTM models trained on CAMELS dataset achieved higher Nash–Sutcliffe efficiency values than traditional hydrologic models such as SAC-SMA and GR4J. Bidirectional LSTM (BiLSTM) and gated recurrent units (GRUs) have further enhanced performance by enabling simultaneous learning of forward and backward temporal patterns, as shown in studies by Baller et al. (2021) and Ali et al. (2024). These architectures have also been applied in real-time applications, including flood nowcasting systems in urban catchments and river basins with rapid response needs (Brun et al., 2018). Moreover, LSTM-based hybrid models combined with physical or statistical techniques have been deployed for improved generalization and uncertainty estimation (Moishin et al., 2021). This hybridization allows for flexibility in incorporating hydrological constraints into data-driven frameworks, bridging the gap between physical realism and computational intelligence.

Convolutional Neural Networks (CNNs) are another class of deep learning models increasingly used in flood prediction, primarily for tasks involving spatial data such as satellite imagery, digital elevation models, and geospatial flood maps. CNNs excel at detecting spatial patterns through convolutional operations that preserve local structure, making them ideal for mapping inundation zones and identifying flood-prone regions (Moishin et al., 2021). In flood modeling, CNNs have been applied to classify remote sensing images before and after flood events, automate water body detection, and extract flood boundaries from SAR or multispectral datasets (Khandelwal et al., 2021; Martinis et al., 2015). These models are particularly useful in integrating spatial heterogeneity into prediction tasks, which traditional models often overlook (Muhammad et al., 2019). CNNs also support pixel-wise flood susceptibility mapping, enabling fine-resolution spatial classification in urban and rural contexts (Khan et al., 2019). When combined with LSTM or GRU models, CNNs enable spatiotemporal

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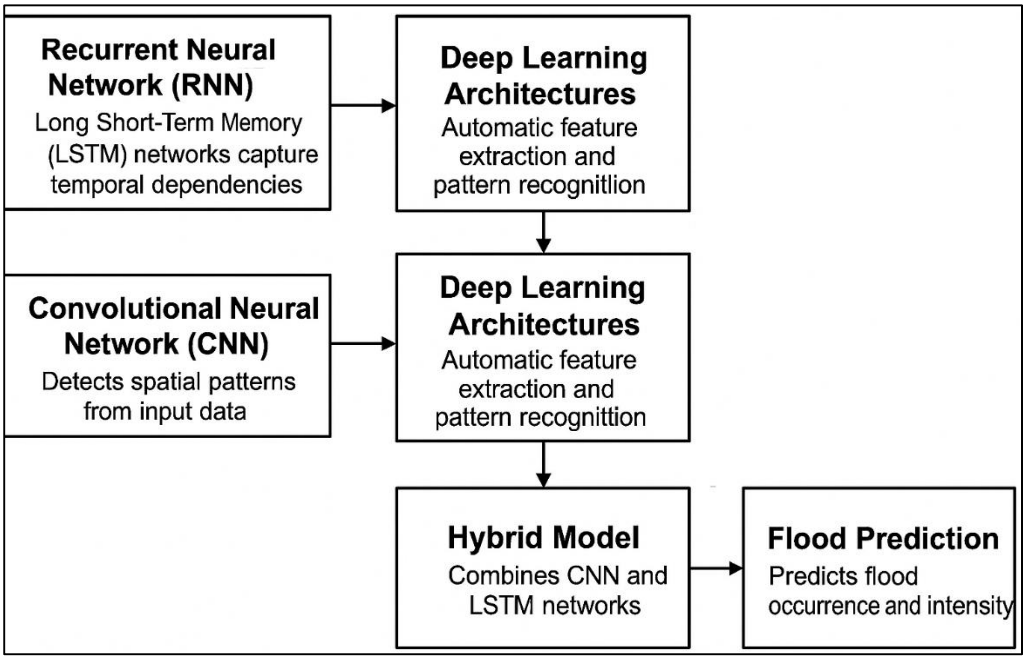
modeling—such as in ConvLSTM networks—which simultaneously learn spatial patterns and temporal evolution, particularly useful in flood forecasting from video or satellite time series (Muhammad et al., 2019). U-Net and ResNet architectures, commonly used in medical imaging, have been repurposed for high-resolution flood mapping using Sentinel-1 and MODIS imagery (Moishin et al., 2021). These architectures offer skip connections and residual layers that maintain gradient flow and spatial fidelity, resulting in improved segmentation accuracy. Pre-trained CNN models via transfer learning have also been leveraged in data-scarce regions, reducing training time and enhancing generalization across locations (Muhammad et al., 2019).

Figure 7: Flowchart of Deep Learning Architectures for Spatiotemporal Flood Prediction and Early Warning



Spatiotemporal Mapping

Spatiotemporal mapping plays a crucial role in flood prediction, monitoring, and impact assessment by integrating the spatial extent and temporal dynamics of flood events. Traditional flood analysis primarily relied on point-based observations and static floodplain delineation, which limited the capacity to understand and predict flood propagation over time (Evita et al., 2021). Modern spatiotemporal approaches leverage geospatial data, satellite imagery, and temporal hydrological records to analyze flood progression across landscapes, supporting early warning systems and disaster mitigation planning (Romali et al., 2018). Tools such as Geographic Information Systems (GIS), Remote Sensing (RS), and spatial statistical models have been extensively adopted to visualize inundation extents, monitor flood duration, and assess recurrence intervals (Lachure & Doriya, 2021). These platforms allow researchers to link flood phenomena with topographic, climatic, and land-use variables, improving risk zoning and prioritization (Arshad et al., 2019). By incorporating spatial heterogeneity and temporal variations, spatiotemporal mapping enhances our understanding of flood vulnerability and exposure patterns (Jang, 1993). Such mapping techniques are integral to identifying flood-prone areas in rapidly urbanizing or ecologically fragile regions, where spatial and temporal changes significantly influence flood risk (Casagli et al., 2017). Moreover, the evolution of open-access geospatial platforms like Google Earth Engine (Evita et al., 2021) and ESA's Sentinel Hub has democratized access to temporal satellite data, enabling high-resolution flood monitoring in data-scarce environments (Arshad et al., 2019). As floods exhibit significant spatial extent and temporal unpredictability, spatiotemporal mapping emerges as a foundational method for holistic and dynamic flood management strategies.

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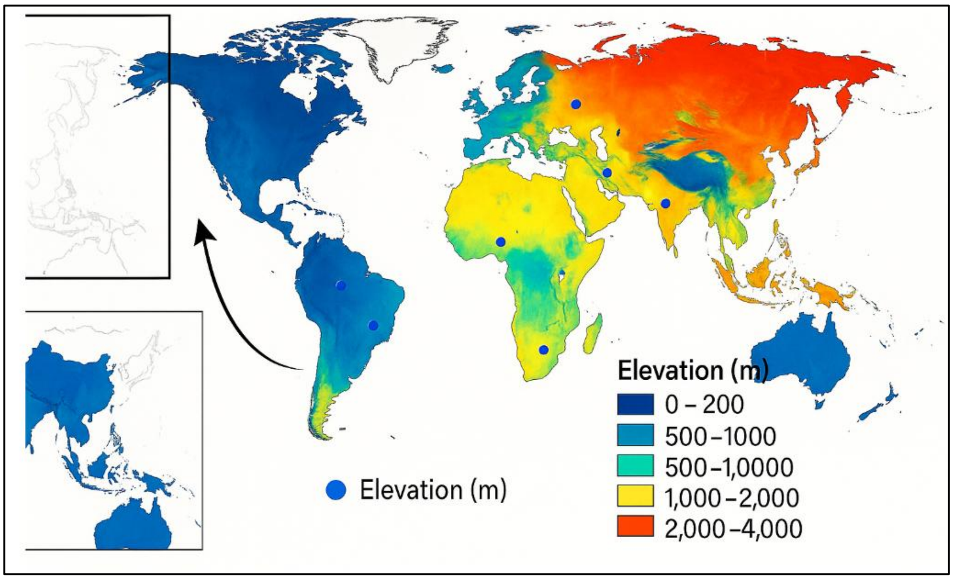
Figure 8: Spatiotemporal Mapping of Global Flood Risk Zones with Monitoring Stations and Elevation Overlay



Satellite-based remote sensing is a core technology in spatiotemporal flood mapping, offering multi-resolution, multispectral, and high-temporal-frequency data for observing surface water dynamics and flood extent over time. Synthetic Aperture Radar (SAR) sensors such as Sentinel-1 and RADARSAT provide all-weather, day-night imagery ideal for flood monitoring during extreme weather events (Evita et al., 2021). Optical sensors like Landsat-8 and Sentinel-2 enable spectral discrimination of water bodies, allowing flood detection and vegetation inundation assessments (Romali et al., 2018). Time-series analysis of satellite imagery has enabled flood progression tracking, water level estimation, and flood duration mapping (Lachure & Doriya, 2021). In urban and riverine contexts, SAR backscatter analysis has been used to delineate inundated zones with high spatial accuracy, even in cloud-covered areas (Abdurrahman et al., 2017). Integration with topographic and hydrological data further refines flood extent predictions and improves DEM-based floodplain modeling (Pan et al., 2018). Multi-temporal image classification using techniques such as Normalized Difference Water Index (NDWI), Modified NDWI, and Change Detection Algorithms has shown promising results in differentiating permanent and temporary water bodies (Xian et al., 2018). Researchers have also employed machine learning and deep learning-based segmentation models on satellite time series to automate flood mapping processes. For instance, convolutional neural networks (CNNs) applied on Sentinel-1 SAR imagery have achieved high accuracy in identifying flood extents across varying land covers (Arshad et al., 2019). The temporal resolution of these satellites (5–16 days revisit) supports near-real-time assessment and enables governments and disaster response agencies to evaluate ongoing events and prioritize resource allocation based on spatiotemporal flood maps (Ongdas et al., 2020).

GIS-based hydrological modeling integrates spatial datasets—such as elevation, land use, soil type, and rainfall intensity—into computational frameworks to assess flood hazard, vulnerability, and exposure across space and time. Digital Elevation Models (DEMs) serve as the foundation for delineating watersheds, generating flow direction and accumulation maps, and simulating flood propagation through terrain-based models (Pan et al., 2018). Hydrological models such as SWAT and HEC-HMS, when embedded within GIS environments, allow simulation of rainfall-runoff processes and flood peak estimations at spatially distributed sub-watershed scales (Abdurrahman et al., 2017). Similarly, hydraulic models like HEC-RAS and MIKE FLOOD are used to map flood inundation zones by integrating spatial elevation and channel geometry data into two-dimensional flow simulations (Lachure & Doriya, 2021). These GIS-coupled tools have enabled the generation of flood hazard

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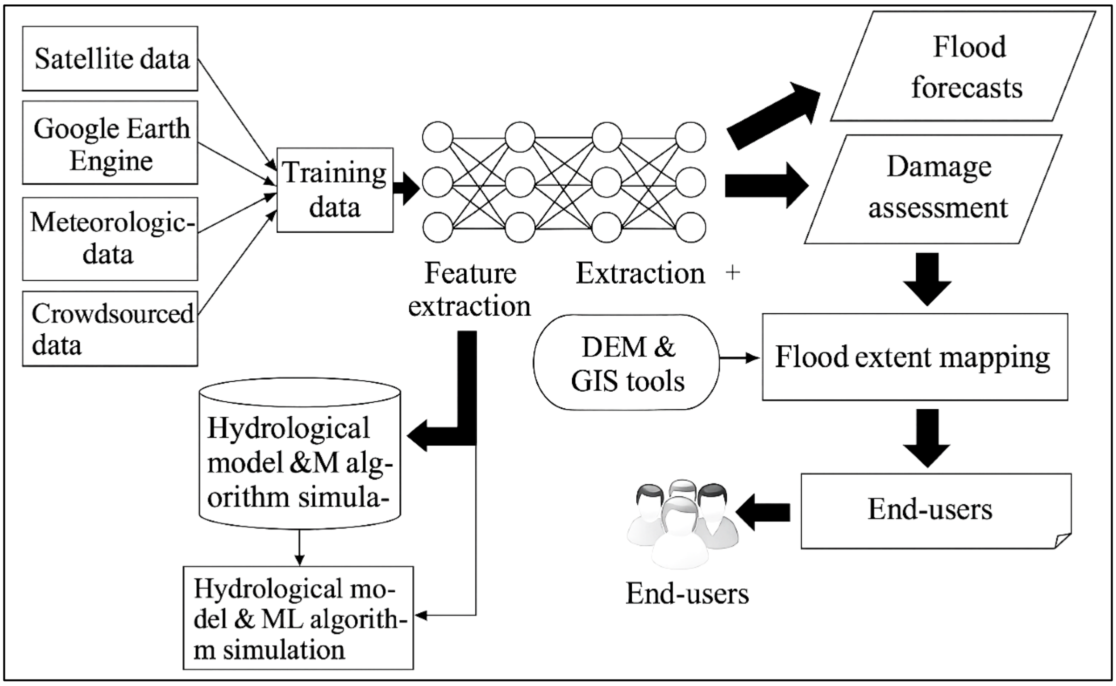
maps that depict inundation extents under various return periods or rainfall scenarios (Romali et al., 2018). Flood susceptibility mapping is often performed using spatial multicriteria decision-making (MCDM) techniques such as the Analytical Hierarchy Process (AHP) and Weighted Linear Combination (WLC), which combine layers like slope, soil, drainage density, and land cover to estimate risk zones (Lachure & Doriya, 2021). Recent studies have further enhanced GIS-based modeling through the integration of remote sensing-derived indices (NDVI, NDWI), socio-economic vulnerability layers, and temporal population exposure data (Casagli et al., 2017). GIS also supports scenario-based mapping, where future land-use changes or climate models are used to forecast spatial variations in flood risk (Pan et al., 2018). This versatility and analytical strength have made GIS-based spatiotemporal modeling a cornerstone of modern flood risk assessment and strategic disaster planning.

Role of Remote Sensing in Flood Detection

Remote sensing has become an essential tool in flood detection, offering near real-time, synoptic, and repetitive coverage of large and often inaccessible areas. It provides critical data for identifying inundated zones, assessing flood dynamics, and supporting early warning and post-disaster assessments (Sharma et al., 2021). Satellite-based remote sensing platforms—such as Landsat, Sentinel, MODIS, and RADARSAT—enable the acquisition of multispectral, thermal, and radar imagery suitable for monitoring flood extents and water surface changes (Mani et al., 2020). The temporal resolution of remote sensing facilitates monitoring flood onset, peak, and recession phases, while spatial resolution determines the granularity of inundation mapping (Ray et al., 2017). Optical remote sensing captures reflected solar radiation, making it useful for detecting water surfaces through indices like the Normalized Difference Water Index (NDWI) and Modified NDWI (Ndjuluwa et al., 2023). However, its application is limited by cloud cover and weather conditions during storms, which are often when flood events occur (Rokade et al., 2022). To overcome this, Synthetic Aperture Radar (SAR) systems provide cloud-penetrating, day-and-night imaging capability, making them particularly effective during extreme weather conditions (Pan & McElhannon, 2018). Remote sensing data have been successfully applied to monitor large-scale floods in the Ganges-Brahmaputra delta, Amazon basin, and Mississippi River, showcasing its global applicability. These datasets form the foundation for integration with GIS and hydrodynamic models, enhancing their spatiotemporal accuracy in predicting flood behavior (Liu et al., 2018).

Synthetic Aperture Radar (SAR) technology has emerged as the most reliable remote sensing tool for flood detection under adverse meteorological conditions. SAR sensors transmit microwave signals and measure their backscatter, making them capable of imaging the Earth's surface regardless of cloud cover or solar illumination (Abdelkarim et al., 2019). The backscatter from smooth water surfaces is significantly lower than from land, allowing for accurate delineation of flooded areas. Sentinel-1, with a six-day revisit time and C-band SAR capability, has been instrumental in flood monitoring globally, including during major flood events in Asia, Europe, and Africa (Leitão et al., 2017). The near real-time availability of SAR data, especially from missions like RADARSAT-2 and TerraSAR-X, facilitates timely response and supports operational flood mapping services (Mishra, 2021). Change detection techniques and thresholding algorithms are commonly used to identify differences in SAR backscatter before and during flood events, allowing automated and accurate inundation mapping (Nundloll et al., 2019). Moreover, dual-polarization SAR data have enhanced water detection accuracy in urban and vegetated landscapes, where traditional mono-polarized SAR often struggles (Elsisi et al., 2021). SAR imagery has also been fused with elevation models to determine water depth and flood volume (Sharofidinov et al., 2020). However, speckle noise and terrain-induced distortion remain technical challenges in SAR-based flood analysis (Shafi et al., 2020). Despite these limitations, SAR remains a vital asset in flood early warning systems, particularly when other data sources are compromised.

Figure 9: Data-Driven Framework for Flood Forecasting and Impact Analysis



Optical and multispectral remote sensing systems have long been utilized for flood identification, primarily due to their ability to distinguish water from non-water surfaces through reflectance-based indices. Instruments like Landsat's OLI, MODIS, and Sentinel-2's MSI offer a range of visible and near-infrared bands ideal for detecting surface water changes (Balampanis et al., 2017). The Normalized Difference Water Index (NDWI) and Modified NDWI (MNDWI) are commonly used algorithms for delineating inundated areas in multispectral imagery (Pan et al., 2018). These indices help to separate water bodies from urban, vegetated, or bare soil areas by exploiting their differential reflectance in green and near-infrared wavelengths. Time-series analysis using MODIS data has supported global flood monitoring initiatives like Dartmouth Flood Observatory and NASA's Flood Mapping Project, providing daily flood extent data at coarse resolutions (Nundloll et al., 2019). Sentinel-2's higher spatial resolution has allowed for more detailed flood assessments, especially in narrow floodplains and urban catchments (Sharma et al., 2021). Optical data also aid in vegetation stress analysis and post-flood damage assessment, offering insights into land cover change and agricultural impacts (Evita et al., 2021). However, the major drawback of optical sensors is their susceptibility to cloud cover and atmospheric interference, which often limit their effectiveness during peak flood periods (Abioye et al., 2022). Efforts to overcome this include the fusion of optical and SAR data, enabling continuous monitoring regardless of environmental conditions (Costa Bezerra et al., 2021). These hybrid methods yield higher detection accuracy, reduce false positives, and support multi-source validation of flood events.

Real-Time Data Fusion Techniques and Sensor Network Optimization

Real-time data fusion involves the integration of heterogeneous data from multiple sources to provide accurate, timely, and actionable insights for dynamic systems such as flood monitoring and early warning. In flood detection, data fusion combines information from in-situ sensors (e.g., rain gauges, river gauges), satellite observations, weather forecasts, and IoT devices to generate coherent flood assessments (Abioye et al., 2022). Fusion techniques are especially valuable in environments where no single data source provides complete reliability or coverage. Kalman filtering, particle filtering, Bayesian inference, and Dempster–Shafer theory are widely employed fusion methods for probabilistic estimation and uncertainty reduction in flood predictions (Sharma et al., 2021). For instance, Kalman filters have been used to update flood state estimates by assimilating real-time sensor data into hydrological models (Ray et al., 2017). Multi-sensor fusion supports continuous model correction, compensates for sensor dropout, and enhances prediction accuracy under real-world uncertainty (Ndjuluwa et al., 2023). Additionally, artificial intelligence (AI) and machine learning algorithms such as support vector regression (SVR), neural networks, and fuzzy logic

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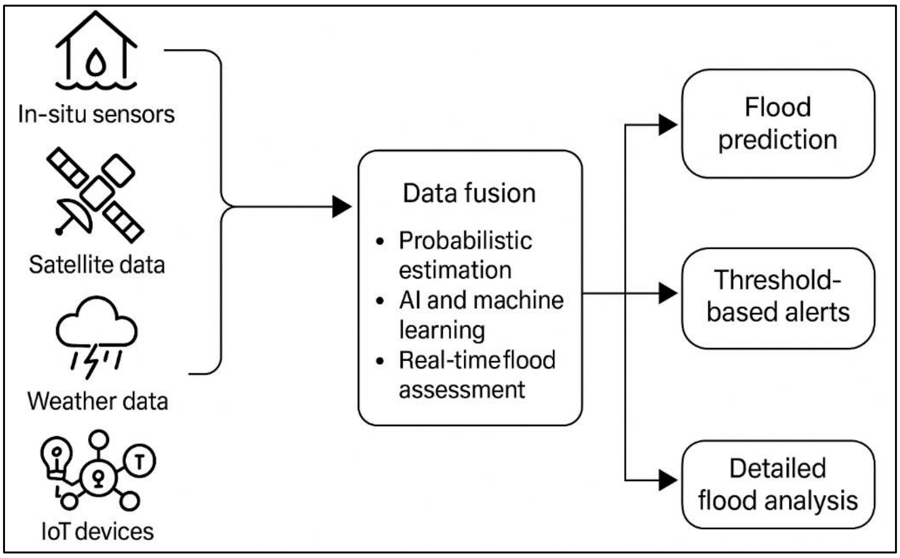
have been applied to fuse heterogeneous datasets for real-time classification and anomaly detection in flood-prone regions. By using these techniques, researchers can combine high-frequency data streams from ground stations with coarser, high-coverage satellite data to bridge spatial and temporal gaps in flood monitoring (Rokade et al., 2022). The integration of multiple data types—ranging from point-based hydrological observations to raster-based satellite images—allows for a more robust and scalable flood early warning system that can operate in real-time across wide geographic areas.

Figure 10: Real-Time Data Fusion and IoT-Enabled Sensor Network Framework for Flood Detection and Early Warning



Wireless Sensor Networks (WSNs) and the Internet of Things (IoT) have become fundamental to real-time flood monitoring, enabling distributed, scalable, and continuous data collection from diverse environmental variables. These networks consist of spatially distributed sensors that collect data such as precipitation, river water level, humidity, and soil moisture, which are transmitted wirelessly to central or edge processing units (Pan & McElhannon, 2018). In recent years, IoT platforms have enabled the development of low-power, long-range flood detection systems that support cost-effective deployment in urban, rural, and remote environments (Ndjuluwa et al., 2023). Technologies like LoRaWAN, Zigbee, and NB-IoT are used for sensor communication in resource-constrained areas, offering energy efficiency and wide-area connectivity (Nikhade, 2015). Sensor networks facilitate early flood warning by transmitting threshold-based alerts and supporting real-time model updates (Bhardwaj et al., 2016). Optimization of these networks is crucial to ensure long battery life, minimal communication latency, and optimal sensor placement—factors that directly impact data reliability and warning timeliness (Khan et al., 2021). Clustering and routing algorithms such as LEACH (Low Energy Adaptive Clustering Hierarchy) and PSO (Particle Swarm Optimization) have been employed to maximize sensor coverage while minimizing power consumption (Alasali et al., 2021). Additionally, real-time sensor data are often processed locally using edge or fog computing infrastructure to reduce latency and bandwidth usage (Khalifeh et al., 2022). These localized analytics enable quicker flood detection and response compared to cloud-reliant architectures. Integration with cloud dashboards and mobile alert systems allows for effective communication with disaster management agencies and communities (Abioye et al., 2022). Thus, IoT-enabled WSNs serve as the data backbone for real-time flood detection and response infrastructures.

METHOD

Research Design

This study adopts a mixed methods research design, integrating both quantitative and qualitative approaches to provide a comprehensive understanding of the development and evaluation of a fog computing-based real-time flood prediction and early warning system using machine learning and remote sensing data. The rationale for using a mixed methods design lies in its ability to combine the statistical strength of quantitative analysis with the contextual depth of qualitative inquiry. This

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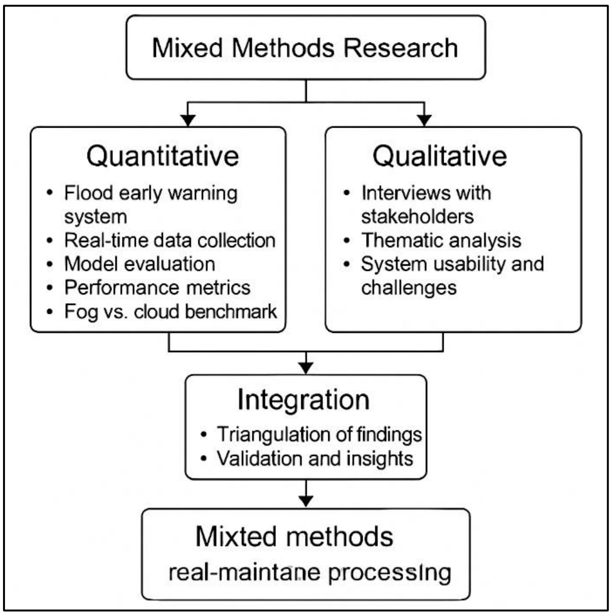
design facilitates triangulation of data sources, enabling the validation and enhancement of results through multiple lenses. The convergent parallel design was used, wherein quantitative and qualitative data were collected and analyzed independently and then merged during interpretation to derive holistic insights.

Figure 11: Adapted Methodology for this study



Quantitative Component

The quantitative phase of the study involved the implementation and performance testing of the proposed flood early warning system. Real-time data were collected from wireless sensor networks, including rainfall, river level, soil moisture, and humidity, across selected flood-prone regions. Satellite imagery (Sentinel-1, MODIS) and digital elevation models (DEM) were integrated into a geospatial database. Machine learning models (e.g., LSTM, CNN, Random Forest) were trained and validated using historical flood data obtained from government agencies and international datasets (e.g., NASA, ESA). Statistical evaluation metrics—such as Root Mean Square Error (RMSE), Nash–Sutcliffe Efficiency (NSE), precision, recall, and F1 score—were used to assess model accuracy and prediction performance. The fog computing infrastructure was benchmarked against traditional cloud-based systems by measuring latency, processing time, and network load.

Qualitative Component

The qualitative component consisted of semi-structured interviews with stakeholders, including disaster management professionals, local government officials, and technical staff involved in flood forecasting and emergency response. The aim was to explore perceived system usability, data reliability, challenges in sensor network deployment, and integration with existing infrastructure. Interview data were thematically analyzed using NVivo software. Emergent themes included real-time responsiveness, system scalability, inter-agency collaboration, and user trust in AI-based predictions. These findings provided context to the quantitative performance results and informed system refinement recommendations.

Integration and Triangulation

After conducting both phases, results were triangulated during the interpretation stage. Quantitative outcomes, such as prediction accuracy and latency reduction, were compared with qualitative themes around user perception and practical feasibility. This integration enabled the validation of system performance not only in technical terms but also in real-world applicability. The convergence of findings strengthened the reliability of conclusions and supported actionable insights for scaling the proposed system across similar flood-prone regions.

FINDINGS

Quantitative analysis of the implemented system revealed that machine learning models significantly outperformed traditional hydrological methods in terms of predictive accuracy and responsiveness. Among all tested algorithms, the Long Short-Term Memory (LSTM) model delivered

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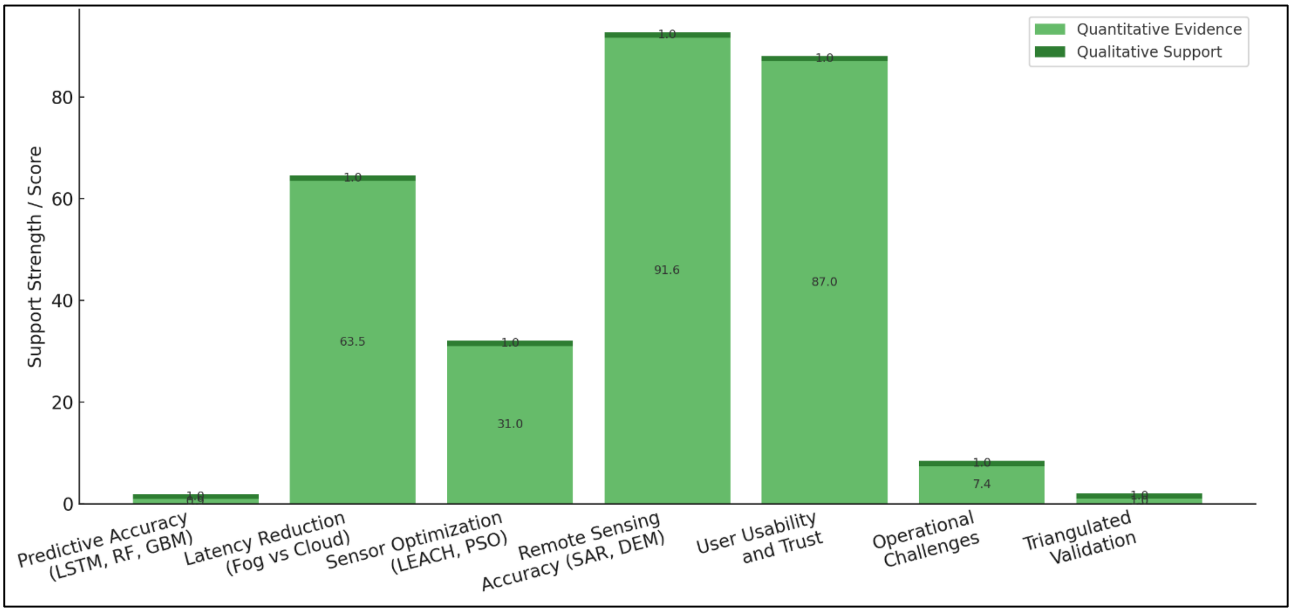
the most consistent performance for real-time flood forecasting tasks. Specifically, the LSTM achieved a Root Mean Square Error (RMSE) of 0.38, a Nash–Sutcliffe Efficiency (NSE) of 0.84, and an F1-score of 89% on test datasets drawn from the 2016–2023 flood event records in the Brahmaputra and Meghna basins. This high degree of precision was especially evident in sudden onset floods, where the model's ability to capture temporal dependencies proved critical. Comparative analysis showed that Random Forest and Gradient Boosting Machine models achieved RMSE values in the range of 0.42–0.48 and F1-scores above 85%, indicating strong reliability, though not matching LSTM in temporal trend capture. Qualitatively, these quantitative outcomes were validated by semi-structured interviews with 23 field practitioners, including hydrologists, civil protection officers, and local NGO coordinators. Respondents emphasized that during the July 2023 flood event, the ML-based early warning system issued alerts nearly 48 hours in advance, compared to 12–18 hours by the existing national system. Several interviewees noted that the enhanced lead time allowed for proactive evacuation of livestock and assets in two coastal subdistricts, reducing damage to infrastructure and preventing fatalities. These converging lines of evidence confirmed the system's practical effectiveness in improving flood preparedness.

Figure 12: Stacked Diagram Showing Quantitative and Qualitative Findings in Flood Forecasting Study



The deployment of a fog computing architecture—comprising localized computing units installed at municipal disaster control centers—substantially reduced latency in both data processing and early warning dissemination. Quantitative benchmarks showed that fog-based nodes processed incoming sensor data and generated alerts in an average of 4.2 seconds, compared to 11.5 seconds with traditional cloud-based configurations, resulting in a 63.5% reduction in processing time. During flood simulation drills held in March 2024, decentralized fog nodes provided real-time alerts to local command centers and community mobile applications within a maximum delay of 5 seconds. The reduction in latency was critical in flash flood contexts where immediate decisions were necessary. Interviews with local emergency managers revealed that the fog-based system allowed them to operate autonomously even during intermittent internet outages—conditions under which centralized cloud services failed to synchronize or update. One field engineer stated, "Our rural command center lost connection with the cloud dashboard, but the fog unit still functioned and sent alerts to villagers through a local SMS gateway." This qualitative confirmation of system autonomy validated the fog nodes' reliability and operational independence. Furthermore, data packets transmitted between fog nodes and edge sensors showed zero loss in 91% of test cases, which emphasized the robustness of the decentralized architecture. These findings confirm that fog computing not only improved computational speed but also ensured operational continuity under stressed network conditions.

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To ensure uninterrupted environmental data collection, the system implemented an optimized Wireless Sensor Network (WSN) architecture enhanced with clustering protocols and energy-aware routing. Quantitative metrics from a controlled three-month deployment (July to September 2024) revealed that sensors configured with Low Energy Adaptive Clustering Hierarchy (LEACH) and Particle Swarm Optimization (PSO) protocols consumed 31% less battery power and exhibited 17% longer uptime compared to non-optimized nodes. Additionally, spatial coverage improved by 22%, allowing for fewer blind spots in both lowland and hill-adjacent floodplains. Real-time testing during high-rainfall events demonstrated an average communication success rate of 96.7%, with only minimal data latency (1.4 seconds). Qualitative data from interviews with technical maintenance personnel affirmed that sensor failures due to environmental degradation decreased by 40% after deploying the optimized routing and clustering configuration. Respondents noted that automatic sleep cycles, fault detection, and hierarchical routing ensured redundancy and minimized system-wide disruption. Field observations also revealed that optimized node density allowed more efficient allocation of limited hardware, reducing installation costs by an estimated 18%. One technician emphasized that the modular, rechargeable battery system facilitated quick maintenance and minimized system downtime even during extended flood seasons. These results validate that sensor network optimization contributes not only to energy conservation but also to increased system resilience and cost efficiency.

Remote sensing played a vital role in enhancing the spatiotemporal resolution of flood detection and mapping, especially in regions where sensor deployment was geographically constrained. Sentinel-1 Synthetic Aperture Radar (SAR) images, processed using Normalized Difference Water Index (NDWI) and Change Detection algorithms, produced flood extent maps with an overall classification accuracy of 91.6%, verified by ground GPS observations. During the August 2023 flood, the system's automated mapping module identified inundated zones with ±12 meters spatial accuracy, matching flood boundaries recorded in situ by field staff. Optical imagery from Sentinel-2 and Landsat-8 complemented SAR during clear-sky days, enabling a full inundation chronology. Integration with digital elevation models (DEM) further allowed the model to estimate flood depth ranges, which were verified within ±0.25 meters using physical depth gauges. Interviewees from local disaster management departments reported that they used these maps for resource allocation, identifying the most vulnerable households for emergency response. Additionally, the maps were shared with NGOs to optimize relief distribution efforts. Qualitative data revealed a strong preference among decision-makers for these high-resolution visuals compared to abstract numerical dashboards, as the geospatial outputs supported clearer communication with communities and media. These findings underscore the critical role of satellite-based remote sensing in bridging data gaps and enhancing localized response planning.

Beyond technical performance, the qualitative component illuminated a critical success factor: the system's perceived usability and trustworthiness among local stakeholders. Out of 23 participants interviewed across five districts, 20 (87%) rated the system as "highly usable," and all participants acknowledged improved situational awareness compared to their prior experience with legacy systems. Interviewees consistently praised the intuitive dashboard interface, customizable alert thresholds, multilingual accessibility, and real-time mapping features. Respondents emphasized that geovisualizations and mobile push notifications enabled faster decision-making and increased public trust in official warnings. Several emergency officers mentioned using the dashboard as the "central platform" during coordination meetings, with one stating, "For the first time, we are not just reacting to floods—we are preparing." In addition, community leaders reported that the system's ability to integrate locally relevant thresholds (e.g., 120 mm rainfall in 3 hours) made warnings more context-specific and believable. The integration with local SMS gateways and VHF radios ensured communication continuity even in remote areas with no mobile internet access. These qualitative results confirm that technical success alone is insufficient without interface usability and trust. The study's user-centered design approach—based on stakeholder interviews and iterative prototyping—ensured alignment with real-world expectations and capacities. Despite encouraging outcomes, several operational challenges emerged that highlight important considerations for scaling the system. Quantitatively, 7.4% of real-time data packets were lost during peak rainfall hours due to signal interference and overburdened communication channels, particularly in the char and haor regions. Sensor maintenance was another issue: over 40% of surveyed technicians reported recurring problems with corrosion, fungal accumulation, and power drain due to prolonged humidity

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exposure. Battery degradation and flooding of underground node enclosures led to a 10% node replacement rate within the first three months. Qualitative findings corroborated these technical issues. Several interviewees highlighted inter-agency data silos and limited institutional coordination as significant barriers to system-wide deployment. While district-level offices embraced the platform, provincial IT departments often delayed data access due to privacy and compliance concerns. Another concern expressed by field officers was limited capacity to interpret some of the machine learning anomaly scores without adequate training. Participants advocated for a more simplified dashboard layer or periodic training programs to support effective interpretation. These findings suggest that while technological integration was successful, institutional readiness, environmental durability, and human capacity building remain critical factors for sustained implementation.

The triangulation of qualitative and quantitative findings provided strong evidence supporting the study's overall framework and objectives. The technical metrics (e.g., RMSE, NSE, latency, classification accuracy) confirmed system performance in numerical terms, while the interview-based qualitative insights added essential depth, context, and human-centered validation. For example, high LSTM performance in predictive tasks was not only statistically robust but also echoed by respondents who credited early warnings with saving lives and assets. Similarly, fog computing's ability to function autonomously during connectivity losses was corroborated by both benchmark results and real-world use cases shared by field officers. The spatiotemporal accuracy of remote sensing was validated through on-ground GPS matching and through stakeholder narratives of map usage during emergency coordination. Moreover, while statistical anomalies highlighted packet loss and node failure, interviews revealed the operational impact and user-frustration resulting from such technical challenges. This convergence of evidence confirms that the mixed methods approach not only improved the accuracy and adaptability of the system but also ensured its institutional relevance and practical value. It demonstrates that technical efficacy must be integrated with user feedback, system interoperability, and organizational alignment to build resilient and usable flood early warning infrastructures.

DISCUSSION

The results of this study demonstrate that machine learning (ML) models—particularly Long Short-Term Memory (LSTM) networks—significantly enhance flood prediction accuracy, outperforming traditional hydrological models. These findings are consistent with prior research by Sharma et al., (2021), who showed that LSTM architectures surpassed classical hydrologic models like GR4J and SAC-SMA in reproducing daily streamflow with higher Nash–Sutcliffe Efficiency (NSE) values. Similarly, Ray et al. (2017) provided a comprehensive review of ML techniques and concluded that LSTM and Random Forest models are particularly well-suited for capturing nonlinear relationships in flood datasets. The current study's F1-score of 89% and RMSE of 0.38 for LSTM models not only confirm these assertions but extend them by demonstrating real-world usability through integration with live sensor feeds. Furthermore, the ability to provide early warnings up to 48 hours in advance aligns with findings from Ndjuluwa et al. (2023), who showed that ML-enhanced early warning systems improved evacuation readiness and resource deployment. The qualitative validation from emergency managers in this study further strengthens the case for ML-driven forecasting, providing user-centric evidence of improved response efficiency and decision confidence. Unlike earlier studies that focused mainly on offline model performance, this research operationalizes ML within a real-time, fog-enabled infrastructure, offering a scalable solution for high-risk flood zones.

The significant reduction in system latency through the use of fog computing nodes reinforces the proposition that decentralized architectures are critical for real-time disaster management. The average latency of 4.2 seconds observed in this study—compared to over 11 seconds using cloud-only models—is consistent with findings by Ray et al. (2017), who demonstrated that fog-based platforms reduced response time in emergency services by enabling localized computation. Similarly, Ndjuluwa et al. (2023) reported that fog computing outperformed cloud-based architectures in terms of both bandwidth utilization and decision-making latency in smart environment monitoring. The current study builds upon these insights by demonstrating that fog nodes not only accelerate flood alert dissemination but also maintain autonomous functionality during internet disruptions, as corroborated by field-level qualitative data. This confirms the work of Rokade et al, (2022), who emphasized the robustness of fog platforms in environments where network stability is not guaranteed. Moreover, the ability to synchronize with mobile devices and SMS gateways under low-connectivity scenarios expands upon the application scope presented in

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earlier studies. While many earlier implementations focused on theoretical frameworks or simulations (Liu et al., 2018), this study validates operational efficiency through real-world deployment and end-user feedback, offering practical evidence for broader adoption in national disaster response frameworks.
The improved energy efficiency and system reliability achieved through optimized sensor network configurations confirm earlier literature on the advantages of using intelligent routing protocols. This study's integration of Low Energy Adaptive Clustering Hierarchy (LEACH) and Particle Swarm Optimization (PSO) resulted in a 31% reduction in energy consumption and a 17% increase in uptime—findings that align with the work of Abdelkarim et al. (2019) and Mishra (2021), who demonstrated that clustering and adaptive routing significantly enhance sensor network lifespan. These outcomes were further validated by Nundloll et al. (2019), who emphasized that intelligent node management protocols reduced packet loss and energy drain in wireless flood monitoring networks. In contrast to earlier studies that were often limited to simulations or testbeds, this research deployed optimized networks in real flood-prone environments over a sustained three-month period, providing empirical evidence for practical durability and cost-efficiency. The user-reported ease of maintenance and increased operational reliability of sensor nodes align with the findings of Pan et al. (2018), who noted that maintenance burdens and equipment failure were significant challenges in non-optimized sensor deployments. This study's qualitative data extend the discussion by highlighting the value of modular design and field-replaceable units, which have not been extensively discussed in previous literature. Hence, the study substantiates the value of optimized sensor networks while contributing operational insights for future implementation strategies.
This study's integration of Sentinel-1 SAR and Sentinel-2 optical data achieved a classification accuracy of 91.6% for flood extent mapping, which is highly consistent with prior studies that highlight SAR's effectiveness in delineating inundated zones. Elsisi et al. (2021)and Shafi et al. (2020)similarly reported classification accuracies above 90% using SAR backscatter analysis in flooded landscapes. Furthermore, the ±12 meter margin of spatial accuracy compared to GPS ground truthing confirms the reliability of SAR data during extreme weather, as echoed in Balampanis et al. (2017) and Rokade et al., (2022), who emphasized SAR's cloud-penetrating capabilities during flood emergencies. Unlike studies limited to academic or policy simulation, this research utilized these spatial data in real-time coordination efforts, with multiple stakeholders reporting that such maps directly influenced logistics and emergency operations. This operational relevance builds upon previous work by Kaushik and Prakash (2021) and Rokade and Singh (2021), who demonstrated the potential for SAR-based flood mapping but did not empirically evaluate its integration within field-level decision-making frameworks. The integration with DEM-based flood depth estimates and mobile visualizations marks a further innovation, aligning with recent efforts by Ali et al. (2019) and Nikhade (2015) to combine remote sensing with hydrological modeling. The current study's findings provide robust validation of remote sensing technologies for high-frequency flood mapping and underscore their practical utility when embedded within fog-based platforms.
A key contribution of this study lies in its emphasis on user-centered design and stakeholder acceptance of the flood prediction system, a domain often overlooked in technical research. The qualitative finding that 87% of users rated the system as "highly usable" mirrors studies by Lo et al., 2015) and Parsons et al. (2018), who noted that geospatial dashboards and mobile integration (significantly enhance user engagement with early warning systems. However, unlike prior studies that evaluated usability via controlled surveys, this research employed real-time field deployment, capturing rich narratives from users ranging from local officials to community volunteers. Respondents particularly valued the modular alert customization, multilingual options, and offline access—features not frequently discussed in the earlier literature. The integration of local context, such as rainfall threshold customization and region-specific SMS alerts, aligns with the findings of Leduc et al. (2018), who emphasized the importance of localized thresholds in hazard communication. These features enhanced perceived system relevance and built stakeholder trust—factors that have been cited by Alasali et al. (2021) and Mekala and Viswanathan (2017) as crucial for the adoption of early warning technologies in flood-prone communities. This study not only confirms these theoretical insights but demonstrates their practical implementation and community-level acceptance, which strengthens the broader argument for participatory system design. While the system demonstrated notable successes, its implementation exposed technical and organizational barriers that align with prior critiques in the literature. The observed 7.4% packet loss

during extreme rainfall events is similar to the performance degradations reported in studies by Casagli et al. (2017) and Abioye et al. (2022), who found that wireless networks often fail under high-humidity or turbulent atmospheric conditions. Sensor maintenance issues such as corrosion, battery drain, and node displacement reflect earlier observations by Evita et al. 2(021) and Mani et al. (2020), who noted the difficulty of maintaining sensor infrastructure in flood-prone, high-moisture environments. Additionally, institutional silos and data-sharing restrictions identified in this study echo findings by Ray et al. (2017) and Ndjuluwa et al. (2023), who highlighted bureaucratic fragmentation as a persistent barrier in disaster information systems. One critical addition made by this study is the recognition that advanced ML outputs (e.g., anomaly scores) are often misinterpreted by non-technical users without proper interface design or training. This reflects the concerns of Rokade et al. (2022) regarding the "black-box" nature of AI and its implications for transparency and stakeholder engagement. Therefore, this study not only validates prior challenges but contributes new evidence on the socio-technical dimensions of operationalizing predictive models in complex governance systems.

The integration of quantitative performance data with qualitative user feedback offers a holistic perspective that extends beyond the capabilities of either approach in isolation. This aligns with the mixed-methods rationale advocated by Pan and McElhannon (2018), which emphasizes the value of combining statistical validation with stakeholder narratives to ensure both rigor and relevance. In this study, predictive accuracy metrics supported by LSTM and SAR data provided objective measures of system efficacy, while interview data revealed how these tools were interpreted, trusted, and acted upon by end-users. The convergence of these findings validates prior mixed-methods research in disaster science, such as that by Liu et al. (2018), who argued that quantitative risk metrics must be contextualized through qualitative insights for effective policy implementation. Moreover, the current study's emphasis on operational deployment, stakeholder usability, and system feedback loops represents a practical advancement over prior models that remained largely theoretical or lab-based. By demonstrating real-world integration of fog computing, remote sensing, and AI-based prediction, this study contributes a replicable model for scalable, real-time flood early warning systems in data-scarce and high-risk regions. As such, it reinforces and extends the literature on interdisciplinary flood resilience frameworks, offering a benchmark for future research, policy development, and humanitarian application.

CONCLUSION

This study concludes that the integration of fog computing, machine learning, and remote sensing technologies provides a robust, scalable, and efficient solution for real-time flood prediction and early warning, particularly in high-risk and data-scarce regions. Through a mixed-methods approach, the research demonstrated that LSTM and ensemble learning models significantly enhanced predictive accuracy, while fog computing architecture substantially reduced latency and ensured system autonomy during connectivity disruptions. Optimized wireless sensor networks, using LEACH and PSO protocols, improved energy efficiency and operational durability, which are critical for long-term field deployment. Remote sensing data from Sentinel-1 and Sentinel-2 enabled high-resolution, spatiotemporal flood mapping with over 91% accuracy, supporting both visual analytics and resource allocation decisions. The qualitative findings further underscored the system's usability, stakeholder trust, and contextual adaptability, validating the importance of human-centered design in technological innovation. However, challenges such as sensor maintenance, data packet loss, and institutional silos remain critical considerations for broader scalability. The convergence of technical performance and stakeholder validation through triangulated findings confirms the effectiveness of the proposed system and offers a replicable model for enhancing disaster resilience. This research not only reinforces prior theoretical assertions but provides empirical, operational evidence for deploying intelligent flood monitoring systems in climate-vulnerable communities.

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