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Review Paper

Evolution of Flood Forecasting: A Comprehensive Review of Traditional and Sophisticated Approaches

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ABSTRACT

Flood forecasting is considered critical in the world, where communities, infrastructure, and the environment are placed at significant risk by floods. In this study, a comprehensive analysis is provided of traditional and sophisticated flood forecasting methods with an emphasis on their strengths, limitations, and applicability in different scenarios. Traditional methods, including empirical rainfall-runoff relationships and historical flood data analysis, have been relied upon as foundational approaches to predicting flood events based on historical patterns and local knowledge. However, these methods are often lacking in precision and responsiveness to real-time changes in climate and land use. In contrast, the accuracy and lead time of flood forecasts have been improved through the leveraging of advanced computational models, remote sensing, and machine learning algorithms, deep learning algorithms in modern techniques. Technologies such as hydrodynamic modelling, satellite-based monitoring, machine learning, deep learning and hybrid models have been demonstrated to offer higher predictive capabilities by integrating real-time data and spatial analysis. Case studies from recent flood events are analyzed in this study, with comparisons drawn between the accuracy, efficiency, and adaptability of both approaches. The findings suggest that while traditional methods are valued for their simplicity and low cost, modern forecasting methods provide greater precision and adaptability, which are essential for proactive disaster management in a changing climate. This study recommends a hybrid approach that integrates traditional knowledge with modern technology to enhance the accuracy and dependability of flood forecasting systems.

INTRODUCTION

Flood forecasting plays an essential role in mitigating the impacts of floods by providing early warnings, enabling timely evacuations, and guiding flood management efforts. Over the years, flood forecasting methods have evolved from traditional, physically-based models to modern, data-driven techniques, reflecting advancements in computational power, data availability, and technology. This literature review explores both traditional and modern methods of flood forecasting, examining their applications, strengths, and limitations. Concerns around the world have undeniably been escalated by the increasing frequency, intensity, and geographical reach of natural disasters, driven in part by factors such as climate change, population growth, and urbanization [Tin et al., 2024]. The reliability of forecasts has drastically increased due to advances in meteorological and hydrological models, richer data from satellites, and improved analytical techniques [Jain et al., 2017]. Integrating machine learning into physical models enhances the data collection and processing of remotely sensed data, with cloud computing enabling faster processing and greater computational efficiency for heavy data and model integrations [Byaruhanga et al., 2024].

Traditional flood forecasting methods, such as hydrological and hydrodynamic models, have been the cornerstone of flood management for decades. Practical implementation of sustainable integrated watershed management practices should be carried out throughout the landscape of the catchment, from upstream to downstream areas [Arnold et al., 1998]. The effect of hydraulic parameters on the river's flow characteristics is also predicted using one-dimensional hydrodynamic modeling [AlMansori & Sanker, 2020]. A stepwise cluster analysis hydrological approach can be used to characterize hydrological processes complicated by nonlinear and dynamic relationships, and satisfactory predictions can be provided. [Feng et al., 2021]

In contrast, AI driven flood forecasting techniques, including machine learning and deep learning are data-driven and can analyze vast amounts of information from multiple sources, such as satellite imagery, sensor networks, and historical flood records. The data assimilation method proves highly effective in reducing errors in flood forecasting. [Sandilya, 2020]. Numerical Weather Prediction models have significantly enhanced the capability to predict precipitation. [Shrestha et al., 2012].

This paper presents a comprehensive review of existing flood forecasting models, encompassing traditional, modern, and hybrid approaches. It emphasizes the unique strengths of each method—for instance, the clear physical basis of traditional hydrological models and the predictive accuracy offered by data-driven techniques such as machine learning—while also examining their respective limitations, including issues like high data requirements, model complexity, and limited adaptability. Through this analysis, the study identifies potential for integration, proposing that the fusion of conventional reliability with modern technological flexibility can significantly enhance the accuracy, responsiveness, and overall effectiveness of flood forecasting systems. The low-lying regions in areas are vulnerable to flooding as well as periodic marine transgressions, posing significant environmental and socio-economic challenges [Chothodi & Kuniyil, 2024]. The primary objective is to explore ways to enhance these models to deliver timely and reliable flood forecasts, ultimately minimizing the adverse impacts of floods on vulnerable communities and infrastructure models. Fig 1 illustrates various types of flood forecasting models.

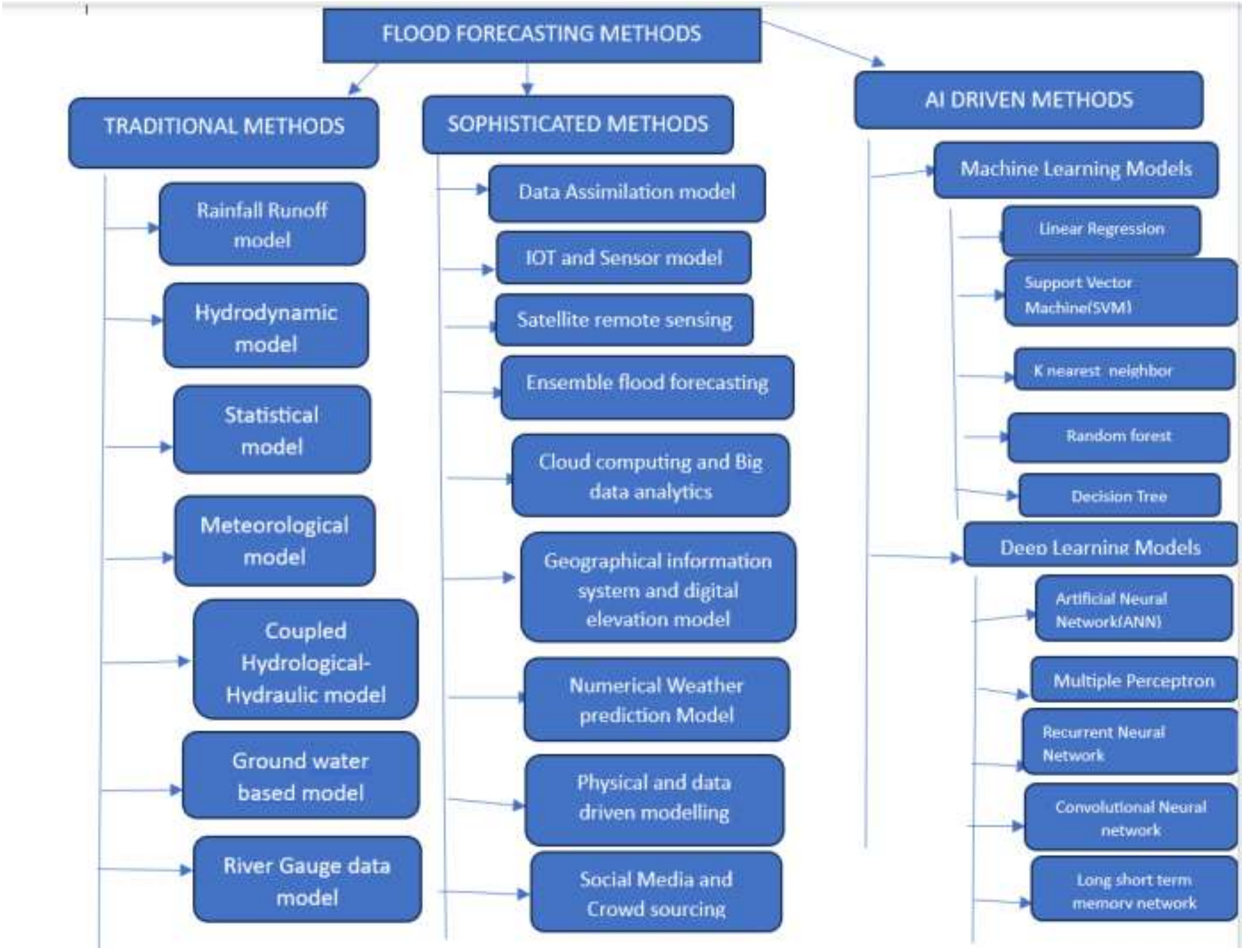


Fig 1: Different types of flood forecasting models

2. Traditional methods and Sophisticated Models in Flood Forecasting

Traditional flood forecasting models are grounded in physically based hydrological and hydrodynamic concepts, employing mathematical equations to replicate processes like rainfall-runoff, river discharge, and water level variations. Models such as Hydrologic Engineering Center – Hydrologic Modeling System (HEC-HMS) and Soil and Water Assessment Tool (SWAT) are appreciated for their ability to realistically represent natural systems and provide physically interpretable outputs. However, they typically demand extensive calibration, high-resolution input data, and significant computational resources. In contrast, sophisticated models encompass data-driven and hybrid techniques, often leveraging machine learning, deep learning, and remote sensing. These modern approaches can process vast datasets, capture complex nonlinear patterns, and enhance forecasting precision and lead time. Despite their advantages, they can be less transparent and require substantial training data. Integrating the strengths of both traditional and sophisticated models holds great potential for developing more reliable, accurate, and efficient flood forecasting solutions.

2.1 Traditional methods

Traditional methods of flood forecasting have long relied on deterministic approaches that utilize historical hydrological data, meteorological observations, and empirical models to predict flood events. These methods use river gauge measurements, rainfall records, and physical models to predict flood likelihood and severity in specific areas. Traditional forecasting methods help assess flood risks but have limitations due to their reliance on historical data, fixed thresholds, and linear assumptions in hydrological processes. Fig2 illustrates various types of traditional flood forecasting models.

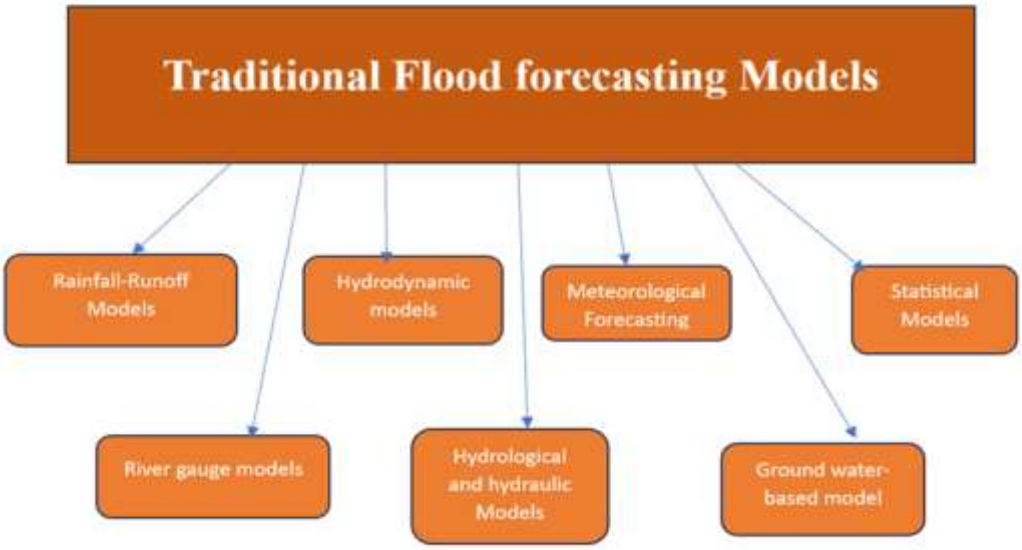


Fig 2: Different types of traditional flood forecasting models

2.1.1 Rainfall-Runoff Models

Rainfall-runoff models are essential tools in hydrology, designed to predict the conversion of rainfall into runoff. This runoff represents water flow generated when stormwater, meltwater, or other sources exceed the soil's infiltration capacity. The Soil and Water Assessment Tool model can be effectively applied to rainfall-runoff analysis through thorough calibration and validation processes. [Reddy & Lingaraju, 2024]. In addition to climate change, the expansion of impervious surfaces due to urban development can significantly disrupt the microclimate and hydrological processes in small catchments. This intensified urbanization exacerbates the impacts on local environmental conditions and water systems. [Muhammad & Muhammad, 2024] A multi-task Decomposition-Integration-Prediction approach has been employed across various regions worldwide for medium- to long-term runoff prediction [Zuo & Yan, 2024]. Applying the Soil Conservation Service Curve Number method, we evaluated the effect of land use and land cover on runoff estimation in the watershed. [Ajith & Barik, 2024]. Flood forecasting is essential for managing floods, especially in Kerala, India, where monsoon floods cause major social, economic, and environmental damage. Kerala's rivers, wetlands, and tropical climate make it highly prone to flooding during the southwest monsoon season [Tripathy et al., 2020].

2.1.2. Hydrodynamic Models

Hydrodynamic models are mathematical models used to simulate the movement of water and other fluids in various environments, such as rivers, lakes, oceans, estuaries, and urban drainage systems. A one-dimensional (1D) hydrodynamic model was developed in HEC-RAS, utilizing a combination of surveyed data, spatially extracted cross-sections, and recorded streamflow data. The model demonstrated improved performance, providing more accurate runoff predictions and better representation of river dynamics when these data were integrated effectively. [Kashfy & Ab Ghani, 2020]. The limitations of 1D-1D models in accurately simulating flood extent and inundation can be addressed through the use of 1D-2D coupled models. [Kourtis & Tsihrintzis, 2017] Numerical modeling using Delft3D software can significantly enhance dredging operations by simulating the transport of sediment deposits during flood events [Pinho & Coelho, 2018]. The HEC-RAS 2D model, after calibration and validation, shows satisfactory performance in simulating flood water levels, with a reasonable correlation coefficient and close alignment between observed and simulated values, indicating its potential for future flood peak prediction. [Garg and Babu, 2023]

2.1.3 Statistical methods

Statistical methods in hydrology and environmental modelling are essential tools for analyzing, interpreting, and predicting natural phenomena based on historical and observed data. The flood prediction error was virtually identical for the direct interpolation method and the flood index procedure [Baidya & Singh, 2024]. Regression analysis as an effective tool for water supply forecasting [Radkov & Yordanova, 2008]. In Regional Flood Frequency Analysis, growth curves that provide flood magnitudes for various return periods are used to estimate flood magnitude and frequency at ungauged sites in various regions of Kerala [Thottumkal & Jothiprakash, 2019]. The flood frequency analysis using the Gumbel Distribution and Weibull plot position method effectively estimates flood magnitudes and recurrence intervals, though its robustness is limited by data availability, highlighting the need for improved data collection and consideration of climate change impacts in future studies. [Sharir et al., 2025]

2.1.4. Meteorological forecasting

Meteorological forecasting involves several cutting-edge methods and technologies. The combination of Numerical Weather Prediction and Hydrological Model is used in the hydrological forecasting system, improving the predictability of flood forecasts [Teja et al., 2023]. The potential for successful hydrological modelling and prediction is demonstrated by the incorporation of the radar-based rainfall forecast [Berenguer & Sempere-Torres, 2013]. Automated time-series flood monitoring can be achieved through the use of multi-source remote sensing imagery [Zhao et al., 2024]. A comparison of Synthetic Aperture Radar-based flood maps with optical data and flood maps generated by the Moderate Resolution Imaging Spectroradiometer underscores the advantages of our data and approach for rapid response and future flood forecasting [Sherpa et al., 2020].

2.1.5. Coupled Hydrological-Hydraulic Models

Hydrological and hydraulic models are essential tools for simulating the movement, distribution, and quality of water across natural and built environments. The MIKE model provides an accurate simulation of the flow, as indicated by the comparison between the estimated and observed stage hydrographs [Kamel, 2008]. Sobek-Rural/Urban offers a complete solution for modelling water systems, including irrigation, drainage, rivers, and sewers, as well as assessing flood risk and planning infrastructure [Dhondia & Stelling, 2004]. Coupled model offers a balance between computational efficiency and accuracy compared to the full hydrodynamic model [Liu et al., 2018].

2.16. Groundwater-Based Models

Groundwater-based models are essential for understanding and simulating the behaviour of groundwater systems, including the flow of water through aquifers, the interaction between groundwater and surface water, and the effects of human activities on groundwater resources. Mod flow model reflects temporal variations in groundwater depletion, which might result from factors like seasonal demand, recharge rates, and aquifer characteristics [Abbood & Mustafa, 2021]. Aquifer water levels are dropping significantly, probably due to over-pumping or lack of recharge [Lamsoge & Katpatal, 2009]. Groundwater and surface water flow calculations quantify hydrologic system inflows, outflows, and storage changes [Markstrom & Niswonger, 2008].

2.1.7. River Gauge Data Models

A River Gauge Data Model for flood forecasting is a crucial component in monitoring river stages (water levels), predicting floods, and issuing early warnings. The statistical hydrological model, employing stepwise cluster analysis, delivers reliable and accurate predictions of complex, nonlinear hydrological processes [Wang & Huang, 2019]. Integrating diverse real-time data sources, including rainfall measurements, soil moisture, wind flow patterns, evaporation, fluvial flow, and infiltration, warrants further exploration to enhance the accuracy and reliability of real-time flood forecasting models [Piadeh & Behzadian, 2022].

Table 1 summarizes information about different traditional modelling studies, focusing on the type of modelling used, the datasets employed, accuracy, study type and the region of study.

Table 1: Studies based on **traditional** models.

References	Model type	Input	Accuracy	Region	Study Type
Tin, D et al., 2024.	Hydrological, Geophysical, biological	climate change, population growth, urbanization,	High	Africa	Regional
Jain et al., 2017	Hydrological, Metrological	Stram flow, Rainfall-runoff, Satellite data	High	India	National
Byaruhanga et al., 2024	Hydrological, Geophysical, biological	Stram flow, Rainfall-runoff, Satellite data	High	Various countries	Multinational
Feng et al., 2021	Hydrological Model	Streamflow	Medium	China	Regional
Chothodi & Kuniyil, 2024	Landslide model	rainfall-runoff	Medium	India	Regional
Muhammad & Muhammad, 2024	Landslide model, hydrological model and ML	rainfall-runoff	Very High	Bangladesh	Regional
Zuo & Yan, 2024	Hydrological Model	rainfall-runoff	Medium	China	Regional
Kashfy & Ab Ghani, 2020	Hydrologic Engineering Center's River Analysis System(HEC-RAS)hydrodynamic model	rainfall-runoff	High	Philippines	Regional
Liu, Z., Zhang, H., & Liang, Q,2018	Coupled Hydrological Hydrodynamic model	rainfall-runoff	Low	UK	Regional
Mazzoleni, M., & Alfonso, L, 2019	Hydrological Model	Sensor data	high	Netherland	Regional
Osman, S., & Abdul Aziz, N, 2018	Stochastic Method	Streamflow	Low	Malaysia	Regional

2.1.8 Advantages of Traditional Models

Traditional flood forecasting models such as rainfall-runoff, hydrodynamic, statistical, and meteorological approaches provide several notable benefits. Their simplicity and transparency make them straightforward to implement, interpret, and communicate, especially for practitioners and decision-makers. These models typically demand low computational power, making them suitable for use in areas with limited access to advanced technology. Being well-established and historically validated, they deliver consistent results in known hydrological conditions. Moreover, their ability to utilize historical and readily available data like rainfall and river gauge record makes them particularly valuable in data-scarce regions. Due to their robustness and reliance on conventional inputs, traditional models are also ideal for long-term flood forecasting and risk assessment applications.

2.1.9 Limitations of Traditional Models

Traditional methods for flood forecasting, while foundational to hydrology and flood risk management, have several limitations that can impact their accuracy, reliability, and timeliness. They depend on fixed equations and assumptions that often fail to reflect the complex, nonlinear behavior of flood events, particularly in the context of shifting climate patterns and land-use changes. These models typically demand extensive calibration and are highly sensitive to the accuracy and availability of input data, making them less effective in regions with limited or unreliable datasets. Moreover, their capacity for real-time forecasting is constrained, and they often struggle to incorporate modern data sources such as remote sensing or high-resolution meteorological inputs. Consequently, traditional methods may lack the flexibility and precision required for forecasting in diverse and rapidly changing hydrological settings. Real time models can produce accurate hindcasts when rainfall is uniformly distributed across the drainage basin. [Perumal & Sahoo, 2007]. Flash flood forecasts account for the inherent limitations and uncertainties in both meteorological and hydrological aspects of forecasting systems. [Collier, 2007].

2.2. Sophisticated Methods

Sophisticated flood forecasting methods have evolved to address the limitations of traditional approaches by integrating advanced technologies, real-time data, and sophisticated models that can simulate complex hydrological processes. Sophisticated flood forecasting methods integrate advanced technologies and multidisciplinary approaches to enhance prediction accuracy and timeliness. These methods leverage innovations such as numerical weather predictions, remote sensing, machine learning, and real-time monitoring to improve accuracy, extend forecasting horizons, and provide early warnings for extreme flood events. Fig 3 illustrates various types of Sophisticated flood forecasting models.

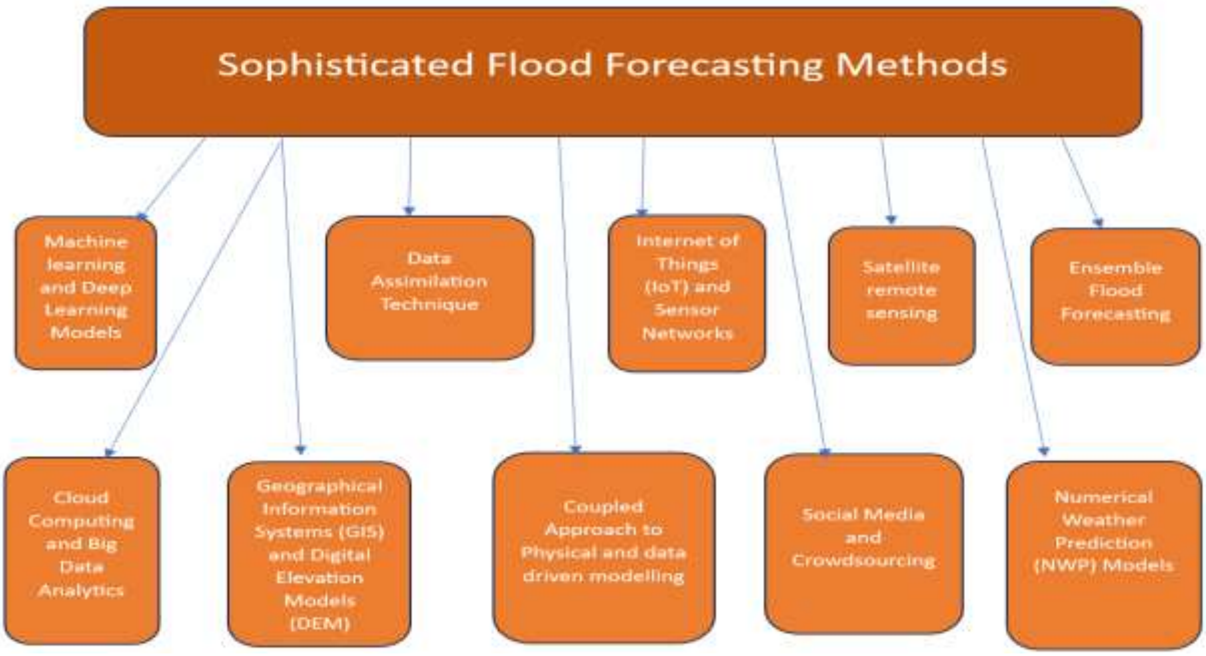


Fig 3: Different types of Sophisticated flood forecasting models

2.2.1 Data Assimilation Methods

Data assimilation techniques play a crucial role in improving the accuracy of flood forecasting by integrating real-time observational data like river levels, precipitation, and other meteorological variables with model predictions. The wavelet-based multi-model Kalman filter is highly effective due to the decomposition capabilities of the wavelet transform, the adaptability of the time-varying Kalman filter, and the strengths of the multi-model approach [Chou & Wang, 2004]. The cost-effective transition of hydrologic data assimilation from research to operations can be facilitated by developing community-based, generic modelling and DA tools or frameworks [Liu & Weerts, 2012]. Data assimilation with the Best Linear Unbiased Estimator (BLUE) method improves peak discharge predictions from the Soil Conservation Service lag and route model [Coustau & Ricci, 2013].

2.2.2 Satellite Remote Sensing

Satellite Remote Sensing has become an indispensable tool for flood forecasting, monitoring, and management. The Global Precipitation Measurement Image Final Run products, available daily and monthly, can detect precipitation well and support long-term analysis [Sun & Sun, 2018]. The use of synthetic aperture radar data helps to understand the extent of flooding and aids in developing more effective planning strategies for risk reduction and management during flood events [Sp & Rahaman, 2021]. The utilization of satellite gravity observations is highly beneficial for studying variations in water storage across regions with areal extents comparable to individual states or river basins [Tiwari et al., 2011].

2.2.3 Numerical Weather Prediction (NWP) Models

Numerical Weather Prediction (NWP) Models coupled with hydrological models provide a powerful framework for improving flood forecasting by integrating atmospheric forecasts with hydrological simulations. Using the WRF-Hydro model, soil moisture, runoff, and precipitation in the fully coupled system exhibited similar spatial trends, whereas evapotranspiration often showed differing patterns. [Wang & Liu, 2020]. Accurate simulation in the Global Flood Awareness System model and better hydrological parameterization is essential for reliably capturing streamflow changes across different runoff regimes [Alfieri & Burek, 2013] . Rainfall forecast biases, particularly in low-resolution models, must be removed before using them for streamflow prediction [Shrestha & Robertson, 2012]. Predictions from the National Centre for Medium Range Weather Forecasting models are evaluated over Kerala to showcase the capabilities of high-resolution models [Ashrit et al., 2020].

2.2.4 Cloud Computing and Big Data Analytics

Cloud Computing and Big Data Analytics have transformed data storage, processing, and analysis, especially in environmental monitoring, flood forecasting, and climate research. Google Earth Engine is a cloud-based platform designed for large-scale geospatial analysis, leveraging Google's vast computational power to address a wide range of critical societal challenges, including deforestation, drought, disasters, disease, food security, water management, climate monitoring, and environmental conservation [Gorelick & Hancher, 2017]. Organizing data and geoprocesses in the Cloud allows integration of services to create customized solutions [Evangelidis & Ntouros, 2014]. Statistical inferences and big data analytics on state-provided ordinal data were used to develop an early warning system [Yusoff & Md Din, 2015].

2.2.5 Geographical Information Systems (GIS) and Digital Elevation Models (DEM)

Geographical Information Systems (GIS) and Digital Elevation Models (DEMs) are vital tools in flood forecasting, risk assessment, and management. This method improves flood extent mapping accuracy, especially for large floods, and provides a practical solution for developing countries with limited resources for traditional flood modelling [Jung et al., 2014]. The cartographic representation supports decision-making processes related to development planning, emergency preparedness, and disaster mitigation through the identification of high-hazard zones. It provides a flexible framework for flood forecasting that requires accurate local data for better flood information management [El Morjan & Ennasr, 2016]. Combining Geographic Information System (GIS) and remote sensing allowed for quick flood-prone area mapping, supporting decision-making for flood mitigation and agricultural water use [Nasr & Akawy, 2023]. The combination of remote sensing data, Geographic Information System (GIS), and Analytical Hierarchy Process (AHP), enhanced with fuzzy-AHP, is an effective way to create accurate predictive maps. [Vilasan & Kapse, 2021]. Sentinel-1 Synthetic Aperture Radar (SAR) data, processed using the Otsu algorithm in Google Earth Engine (GEE) helps map flood areas during disasters, aiding in the protection of lives, infrastructure, and businesses [Tiwari et al., 2020]. Flood vulnerability mapping was validated using 2018 and 2019 flood data, while the weighted overlay method identified suitable areas for flood shelters in moderately vulnerable and vulnerable sub-basins, categorizing them as highly suitable, suitable, moderately suitable, or not suitable [Aju et al., 2024]. The Weighted Overlay Analysis method is used to create a flood hazard map and suggest measures to reduce flood risks in the River Basin [Vinod, 2013].

2.2.6 Coupled Approach to Physical and Data-Driven Modelling

Hybrid Models that couple physics-based models with data-driven approaches represent a significant advancement in hydrological modelling and flood forecasting. combining a machine-learning approach with the Hydrologic Engineering Center - River Analysis System (HEC-RAS) model has enhanced the handling of spatiotemporal uncertainties in conventional flood forecasting methods [Tamiru & Wagari, 2022]. A hybrid hydrological model that integrates the Hydrologic Engineering Center-Hydrologic Modelling System significantly enhances forecast accuracy, particularly for predictions over extended forecasting periods. [Sinh & Nguyen, 2024]. Integrating the Particle Swarm Optimization (PSO) algorithm, Temporal Convolutional Neural Network (TCN) algorithm, and Bootstrap Probability Sampling model demonstrates enhanced applicability and robustness in flood prediction [Yu & Liu, 2024]. Using Hydrologic Engineering Center - River Analysis System (HEC-RAS) software, the findings offer useful tools for future forecasting of natural and human-induced interactions [Aneesh & Thomas, 2024].

2.2.7 Ensemble Flood Forecasting

Ensemble Flood Forecasting is a sophisticated method that uses multiple models to improve flood prediction and handle uncertainties in hydrological forecasts. The Hydrologic Ensemble Prediction Experiment (HEPEX) aims to advance ensemble forecasting capabilities and promote its adoption, highlighting the need to assess the current state of ensemble flood forecasting [Wu & Emerton, 2020]. Deterministic forecasting proved to be accurate, while probabilistic forecasting showed promise with respect to the predicted hydrograph and a quantitative evaluation of confidence levels [Nguyen & Chen, 2020]. The meteo-hydro-AI approach demonstrated slight improvement, highlighting the need for further evaluation with larger samples of extreme flood events, while showcasing its potential for ensemble forecasting of such events [Liu & Yuan, 2024].

2.2.8 Internet of Things (IoT) and Sensor Networks

The Internet of Things (IoT) and Sensor Networks play a pivotal role in modern flood forecasting systems. A scour monitoring system, developed and implemented using a vibration-based array of sensors combined with Internet of Things (IoT) and artificial intelligence (AI), provides real-time scour depth measurements [Lin & Lee, 2021]. An Internet of Things (IoT)-based flood prediction and forecasting model focused on optimizing energy efficiency. [Wajid & Abid, 2024]. Various environmental conditions were monitored using different sensors and transferred to a Google Sheet via IoT technology, allowing the client to remotely analyse the dataset and predict flood risks [Suresh, 2020].

2.2.9 Social Media and Crowdsourcing

Social media and Crowdsourcing have emerged as valuable tools for flood forecasting and management. The flood forecasting system combines weather, water flow, geospatial, and crowdsourced data with machine learning. It uses advanced learning methods and has been tested to accurately predict floods in specific locations and times [Puttinaovarat & Horkaew, 2020]. Low-cost static and dynamic social sensors can improve traditional sensor networks, making flood forecasting more accurate. They also support citizen observatories, where people help collect, evaluate, and share data to improve models and flood resilience [Mazzoleni & Alfonso, 2019]. Crowdsourcing is useful for better coordination, accuracy, and security in relief efforts [Gao & Barbier, 2011].

Table 2 summarizes information about different sophisticated modelling studies, focusing on the type of modelling used, the datasets employed, accuracy, study type and the region of study. India is the region most frequently represented in the studies shown, with rainfall-runoff data being a common dataset used.

Table 2: Studies based on Sophisticated models.

References	Model type	Input	Accuracy	Region	Study Type
Arnold et al., 1998	The Soil and Water Assessment Tool (SWAT) model	moisture	High	US	Regional
AlMansori & Sanker, 2020	NWP model	Streamflow	High	turkey	Regional
Murariu et al., 2010	Digital Elevation Models (DEM)	sedimentation rate, deposition of pollutants, erosion rate	high	Ukraine	Regional
Garg, C. & Babu, A., 2023	HEC-RAS 2D Model	Water level	high	India	Regional
Coustau, M., & Ricci, S,2013	Data assimilation model	rainfall-runoff	medium	France	Regional
Sun, W., & Sun, Y. ,2018	Global precipitation method	rainfall-runoff	high	China	Regional
Sp, D., & Rahaman, S. A.,2021	SAR model	rainfall-runoff	high	India	Regional
Tiwari, V., Wahr, J. M., Swenson, S., & Singh, B,2011	Satellite model	Satellite data	high	India	National
Wang, W., & Liu, J. 2020	Weather Research and Forecasting (WRF-hydro) model	soil moisture, evapotranspiration, generated runoff,	high	China	Regional
Alfieri, L., & Burek, P. A. 2013	GLOFAS model	Streamflow	high	Pakistan	Regional

Shrestha, D., & Robertson, D. 2012	NWP model	Precipitation		Australia	Regional
Gorelick, N., & Hancher, M,2017	Google Earth Engine	Satellite data	Very high	Various countries	Multi national
Evangelidis, K., & Ntouros, K,2014	Geospatial model	Satellite data	high	Various countries	Multi national
Yusoff, A., & Md Din, N,2015	Bigdata model	hydrological data	high	Malaysia	Regional
Jung, Y., Kim, D., & Kim, D,2014	River gauge model	Satellite data	high	Korea	Regional
El Morjan, Z. E. A., & Ennasr, M. S,2016	Geographic Information Systems (GIS) model	Satellite data	high	Morocco	Regional
Nasr, A., & Akawy, A,2023	GIS model	Sensor data	high	Egypt	Regional
Tamiru, H., & Wagari, M, 2022	Hybrid Artificial Neural Network(ANN) and HEC-RAS model	Rainfall, temperature	high	Ethiopia	Regional
Sinh, N. P., & Nguyen, T. H. (F.),2024	Hybrid Long short term memory(LSTM) and Hydrologic Engineering Center - Hydrologic Modeling System (HEC-HMS) model	hydrological data	high	Vietnam	Regional
Yu, Q., & Liu, C,2024,	Hybrid Temporal Convolutional Network (TCN) and Particle Swarm Optimization (PSO)	hydrological data	medium	Thailand	Regional
Wu, W., & Emerton, R,2020	Ensemble model	hydrological data	high	Various countries	Multi national
Abbood, R. T., & Mustafa, A,2021	MODular Finite-difference FLOW (MODFLOW) model	Streamflow	high	Iraq	Regional
Lamsoge, B., & Katpatal, Y,2009	MODFLOW model	Streamflow	high	India	Regional

Markstrom, S. L., & Niswonger, R. G. ,2008	Coupled Ground-water and Surface-water FLOW (GSFLOW) model	Streamflow, Precipitation	high	US	Regional
Wang, F., & Huang, G. ,2019	Suitability of the Height Above Nearest Drainage (SCAH)model	rainfall-runoff	high	China	Regional
Piadeh, F., & Behzadian, K. 2022	Real-Time Flood Forecasting (RTFF) model	soil moisture, wind flow patterns, evaporation, fluvial flow	high	Various countries	Multi national
Perumal, M., & Sahoo, B. 2007	Rain gauge model	rainfall-runoff	high	India	Regional
Collier, C. G,2007	Data assimilation model	rainfall-runoff, metrological factors	medium	UK	Regional
Chou, C.-M., & Wang, R.Y,2004	Kalman filter model	rainfall-runoff	high	Taiwan	Regional
Liu, Y., & Weerts, A,2012	Data assimilation model	hydrological data	medium	China	Regional
Teja et al., 2023	NWP model and Hydrological model	rainfall-runoff	High	India	Regional
Berenguer & Sempere-Torres, 2013	Radar based model	rainfall-runoff	High	Spain	Regional
Zhao, B., Sui, H., & Liu, J.2024	Synthetic Aperture Radar (SAR) model	rainfall-runoff	High	Indonesia	Regional
Kamel, A ,2008	MIKE model	Streamflow	High	Iraq	Regional
Dhondia, J., & Stelling, G. S,2004	Simulations of Overbank flow, Bed level changes, and Erosion/deposition processes(SOBEK)Hydraulic model	Streamflow	High	US	Regional
Kashfy & Ab Ghani, 2020	Hydrologic Engineering Center's River Analysis System(HEC-RAS)hydrodynamic model	rainfall-runoff	High	Philippines	Regional

Kourtis & Tsihrintzis, 2017	MIKE model	rainfall-runoff	High	Greece	Regional
Pinho & Coelho, 2018	Delft3D model	sediment data	High	Portugal	Regional
Baidya & Singh, 2024	Interpolation method	Flood frequency data	High	India	National
Radkov & Yordanova, 2008	Regression method	Streamflow	High	Bulgaria	Regional
Thottumkal & Jothiprakash, 2019	L-moment model	Flood frequency data	High	India	National
Arnold et al., 1998	The Soil and Water Assessment Tool (SWAT) model	moisture	High	US	Regional
AlMansori & Sanker, 2020	NWP model	Streamflow	High	turkey	Regional
Feng et al., 2021	Hydrological Model	Streamflow	Medium	China	Regional
Sandilya, 2020	MIKE model	Streamflow	High	India	Regional
Shrestha et al., 2012	NWP model	Precipitation	High	Australia	Regional
Reddy & Lingaraju, 2024	SWAT model	rainfall-runoff	High	India	Regional

2.2.10 Advantages of Sophisticated System

Flood forecasting has significantly evolved over the years, integrating a diverse range of models and technologies to enhance prediction accuracy, lead time, and spatial resolution. Early systems were built on foundational approaches such as Rainfall-Runoff, Hydrodynamic, and Statistical models, which relied on empirical formulas and physical principles to simulate flood behavior. Accuracy improved with the development of Meteorological and Coupled Hydrological-Hydraulic models, which connect atmospheric inputs with watershed and riverine processes. Groundwater-based models and River Gauge data models offer valuable localized insights but are often limited by sparse spatial coverage and data availability. To strengthen traditional methods, Data Assimilation techniques have been introduced to continuously refine model outputs using real-time observations, while IoT and sensor-based systems provide rapid, field-level data collection for more responsive forecasting. Recent advances in remote sensing and computational technologies have further expanded capabilities—satellite remote sensing enables broad monitoring of key hydrological variables such as precipitation, soil moisture, and water levels, particularly in data-scarce regions. Ensemble forecasting enhances reliability by accounting for uncertainty through multiple scenario simulations, and the use of cloud computing and big data analytics allows for real-time processing of massive datasets, accelerating decision-making. Tools like Geographic Information Systems (GIS), Digital Elevation Models (DEMs), and Numerical Weather Prediction (NWP) models contribute to improved spatial analysis and rainfall forecasting. Moreover, hybrid approaches that combine physically based models with machine learning techniques offer greater adaptability and predictive accuracy. Social media and crowdsourced data have also emerged as valuable resources for real-time, community-driven flood reporting. This evolution underscores the growing need to integrate traditional approaches with cutting-edge technologies to build comprehensive, efficient, and resilient flood forecasting systems.

2.2.11 Limitations of Sophisticated System

Sophisticated flood forecasting models offer high accuracy and timely predictions, but they come with several significant limitations. These models are highly data-intensive, often requiring extensive real-time, high-resolution datasets that may not be readily available in all regions. The integration of multiple advanced technologies—such as machine learning, IoT, satellite remote sensing, and numerical weather prediction—adds layers of complexity, making the systems challenging to calibrate, interpret, and manage. Moreover, the high computational demands and the need for specialized technical expertise can limit their application in resource-constrained settings. Other concerns include the opaque nature of AI-based models, uncertainties in meteorological forecasts, potential sensor malfunctions, and the questionable reliability of crowdsourced data. Therefore, despite their enhanced predictive capabilities, the deployment of these models must be approached with careful consideration of the existing technical, infrastructural, and financial limitations.

3. Artificial Intelligence (AI) driven Models

AI-driven models for flood forecasting leverage sophisticated computational methods such as machine learning, deep learning, and neural networks to process and analyze large volumes of hydrological, meteorological, and spatial data. Unlike conventional models that depend on established physical equations, AI models learn directly from historical datasets, enabling fast and accurate prediction of flood events. These approaches are especially adept at modeling complex, nonlinear relationships between variables and can be applied across diverse regions with minimal calibration. They also excel in incorporating real-time data from technologies like remote sensing and IoT devices. Despite their advantages, AI models typically demand high-quality, extensive datasets and often operate as "black boxes," offering limited insight into the physical processes behind their predictions. Nevertheless, AI represents a transformative advancement in flood forecasting, enhancing accuracy, responsiveness, and adaptability.

3.1 Machine Learning Models

Flood forecasting uses different machine learning models, each designed to handle specific challenges based on data availability, flood complexity, and forecasting needs. Machine learning-based methods have the potential to enhance accuracy while reducing both computation time and the costs associated with model development [Kumar & Biradar, 2023]. Machine Learning models can predict flood stages at a key gauge station using upstream water levels and, if needed, downstream levels to consider backwater effects [Dazzi & Vacondio, 2021]. Heavy Rain Damage Prediction Model, among the selected supervised learning techniques, Random Forest and KNN demonstrated the best performance. [Snehil & Goel, 2020]. The increase or decrease in precipitation convective rates, along with elevated low cloud cover and insufficient vertically integrated moisture divergence, may have influenced the changes in rainfall patterns in India [Praveen & Talukdar, 2020]. The integration of IoT data with machine learning techniques demonstrates improved performance in flood forecasting [Wang, 2022]. Machine learning model for SIFT extraction have the potential to improve accuracy while reducing both computation time and the cost of model development [Suresh Kumar & Alemran, 2022]. Fig 4 illustrates various types of Machine learning models.

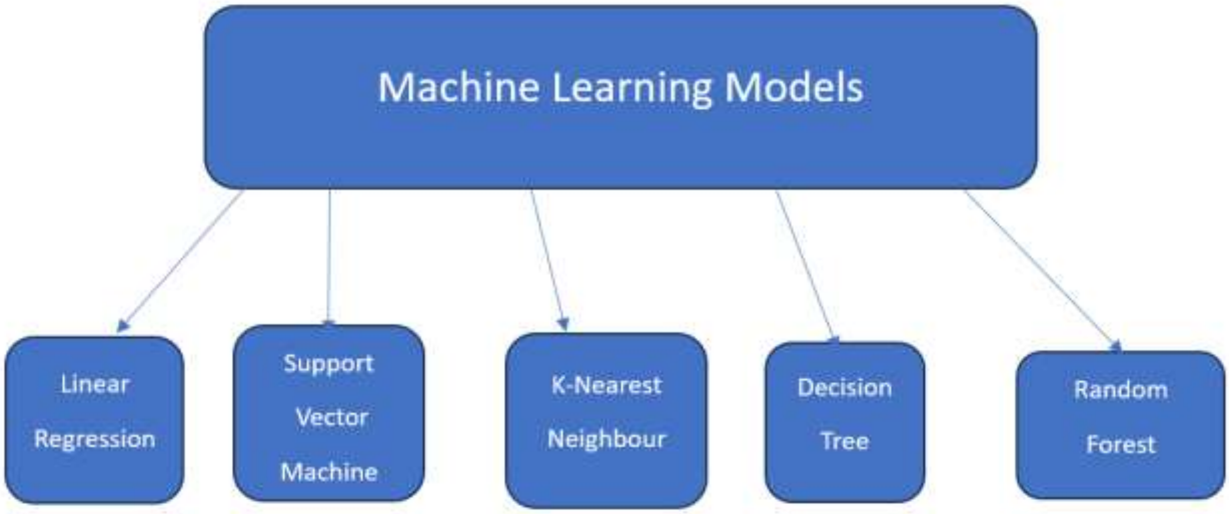


Fig 4: Different types of Machine Learning Models

3.1.1. Linear regression

This model predicts a continuous output like flood discharge level by modelling the relationship between input variables and the output. A regression analysis linked weighted maximum rainfall and maximum streamflow in the River Basin, creating equations using annual maximum daily rainfall, streamflow, and catchment area to rank flood risk for each catchment [Supriya & Krishnaveni, 2015]. An SMS-based warning system sends early alerts with predictions of rising water levels and flow speed [de Castro & Salistre, 2013]. A stochastic flood forecasting model using the stage regression method was applied to the River Basin, with regression coefficients and equations derived based on the least squares principle [Osman & Abdul Aziz, 2018].

3.1.2 Support Vector Machine

Support Vector Machine (SVM) are used for classification or regression by finding a hyperplane that best separates the data into classes. SVM exhibited varying responses to different rainfall inputs, with lighter rainfall producing distinctly different outcomes compared to heavier rainfall [Han & Chan, 2007]. A flood forecasting model usi Supriya &

Krishnaveni, 2015ng SVM, combined with kernel principal component analysis (KPCA) and a boosting algorithm, can significantly enhance forecasting accuracy [Li et al., 2016]. The SVM model offers an operational advantage by extending the forecast lead time during typhoon events [Lin et al., 2013]. A comparative analysis of SVM, Quadratic SVM (Q-SVM), K-NN and Linear discriminant analysis (LDA) algorithms revealed that the Support Vector Machine (SVM) achieved the highest accuracy based on parametric evaluation and training-testing results [Khan et al., 2019]. The Support Vector Machine – Grasshopper Optimization Algorithm (SVM-GOA) model, integrating Support Vector Machine with the Grasshopper Optimization Algorithm, has been developed and evaluated using meteorological data, demonstrating its superiority over SVM alone for accurate flood prediction. [Sahoo & Ghose, 2022].

3.1.3 K-Nearest Neighbors

K-Nearest Neighbors (KNN) is used in flood forecasting to classify or predict flood events based on historical data. It works by comparing new observations with the **K** most similar past events in the dataset, using distance metrics like Euclidean distance. KNN is beneficial for flood forecasting because it is simple, non-parametric, and can adapt to complex patterns in hydrological and meteorological data. Various correlation coefficients are utilized for feature selection, combined with the k-nearest neighbors (k-NN) algorithm, to enhance flood prediction accuracy [Gauhar et al., 2021]. The k-nearest neighbor (KNN) method, coupled with the Kalman Filter (KF), serves as an effective tool for real-time flood forecasting. [Liu et al., 2016]. A hydrodynamic model integrated with the K-nearest neighbors (KNN) algorithm providing critical lead time for emergency decision-making and demonstrating significant potential in flash flood management. [Zhou et al., 2024]. The spatially enhanced KNN-based framework offers an innovative, efficient, and user-friendly approach for assessing risks to the tourism industry amid climate change. [Liu, S. et al., 2021]. The Ensemble-KNN forecasting method, utilizing historical samples, helps mitigate uncertainties arising from modelling inaccuracies. [Yang et al., 2020].

3.1.4 Decision Tree

Decision tree breaks down data by decision rules to model complex relationships between variables and flood events. The IoT-based Decision Tree Algorithm achieves superior classification accuracy. [Vinothini & Jayanthy, 2019]. The integration of decision trees with ensemble models offers reliable estimates of flood susceptibilities, producing trustworthy susceptibility maps for flood early warning systems and mitigation planning [Pham et al., 2021]. Three machine learning algorithms were tested for flood prediction using a historical rainfall dataset. Decision Tree, Logistic Regression, and Support Vector Classification were evaluated, and Decision Tree showed reasonable performance [Khoshkonesh et al., 2024]. Background features affecting predictions are learned, and the model's inner workings are explored using explainable AI modules, with results validated using historical monthly rainfall data from Kerala, India [Kadiyala & Woo, 2022].

3.1.5 Random Forest

Random Forest is a powerful and widely-used machine learning algorithm that belongs to the ensemble learning family. It is an extension of decision trees, combining multiple decision trees to improve model accuracy and reduce overfitting. The performance of the random forest models highlights their effectiveness in accurately filling the gaps in unmapped floodplains [Woznicki et al., 2019]. Various methods, including SVM, Regression, Random Forest, Neural Networks, and Bayesian Networks, are available, with Random Forest and Neural Networks demonstrating superior performance compared to the others. [Sharma et al., 2022]. Using Assam's historical rainfall and geospatial data, machine learning-based flood prediction identified the Random Forest algorithm as the top-performing model [Myrchiang et al., 2023].

The table 3 provides a comparative summary of various machine learning-based flood forecasting models, evaluating them based on modelling type, input datasets, accuracy, computational requirements, lead time, and regional applicability to identify the best-performing model in each case.

Table 3: Studies Based on Machine learning Methods

References	**Modelling type**	**Input Dataset used**	**Accuracy**	**Computational Needs**	**Lead Time**	**Region**	**Best Performed Model**
Nguyen D. T, & Chen,S.T. ,2020	KNN, SVM, Fuzzy inference model	Rainfall - Runoff	Moderate	Low	Fast	Taiwan	KNN
Liu Y., & Yuan X. ,2024	Meteo-hydro-AI, Meteo-hydro	Rainfall - Runoff	High	high	moderate	China	meteo-hydro-AI
Suresh, S,2020	DT	Sensor data	Moderate	low	Fast	India	DT
Kumar, K. S. R, & Biradar R. V,2023	ANN, KNN, LR, SVC, DT, RF	air pressure, humidity, temperature	Moderate	medium	fast	India	LR
Snehil & Goel R,2020	GNBT, KNN	Flood damage data	moderate	Low	Fast	India	KNN
Wang Q,2022	SVR, DT, KNN	IoT data	moderate	medium	Fast	Sweden	KNN
Suresh Kumar V, & Alemran A,2022	SVM, DT, RF	Spatial Data	moderate	medium	moderate	India	SVM, DT
Supriya, P, & Krishnaveni M,2015	LR	Rainfall - Runoff, Stream flow	moderate	low	Fast	India	LR
Han, D, & Chan L,2007	Naïve bayes, SVM	Streamflow	moderate	medium	Fast	China	SVM
Li S., Ma K., Jin Z., & Zhu Y ,2016	SVM	Historical Flood data	moderate	medium	fast	China	SVM
Lin G.-F., Chou Y.-C, & Wu M.-C. ,2013	SVM	Rainfall - Runoff	Moderate	Medium	fast	Taiwan	SVM

Khan. T, Shahid Z, Alam M, Su'ud, M. M, & Kadir. K,2019	SVM, Q-SVM, K-NN, LDA	Rainfall - Runoff	Moderate	medium	fast	Malaysia, Indonesia, Bangladesh France	SVM
Sahoo A, & Ghose. D,2022	SVM-GOA, SVM	meteorological	high	high	moderate	India	SVM-GOA,
Gauhar, N, Das S., & Moury K. ,2021	KNN	Rainfall - Runoff	moderate	low	fast	Bangladesh	KNN
Liu. K, Li. Z, Yao C, Chen. J, Zhang, K., & Saifullah,M. , 2016	KNN	Rainfall - Runoff	moderate	Low	fast	China	KNN
Zhou.N., Hou. J, Chen.H.,et al. ,2024	KNN	Streamflow	moderate	Low	fast	China	KNN
Liu, S., Liu, R., & Tan, N, 2021	KNN	Temporal, spatial data	moderate	Low	fast	China	KNN
Yang, M, Wang, H, Jiang, Y, & et al. ,2020	E KNN	Rainfall - Runoff	moderate	medium	fast	China	E KNN
Vinothini, K, & Jayanthy S ,2019	DT	Streamflow	moderate	Low	fast	India	DT
Pham, B. T et al, 2021	DT	Streamflow	moderate	Low	fast	China	DT
Khoshkonesh.A,Nazari.R,Nikoo, M. R.& Karimi M ,2024	Hydrodynamic Model, ML	Streamflow	high	high	moderate	London	ML
Woznicki et al., 2019	RF	flood-related soil characteristics, land cover	high	medium	moderate	United States	RF
Myrchiang et al., 2023	RF	historical rainfall, geospatial data	high	medium	moderate	India	RF
Wu et al., 2020	GBDT	Rainfall - Runoff	high	medium	moderate	China	GBDT
Kadiyala & Woo, 2022	LR, DT, RF, KNN, SVM	Rainfall data	moderate	low	medium	India	LR

3.1.6 Advantages of Machine learning model

Machine learning (ML) techniques have revolutionized flood forecasting by enabling the modeling of complex, nonlinear relationships among hydrological variables without relying on predefined physical equations. Algorithms like Random Forest (RF) and Decision Tree (DT) are particularly effective at identifying variable interactions and managing incomplete or noisy datasets, making them well-suited for flood prediction and classification tasks. Support Vector Machines (SVM) deliver high accuracy in binary classification problems such as flood versus no-flood scenarios, especially where data is limited. While Linear Regression is a simpler method, it remains useful for short-term forecasting of water levels and discharge in data-rich environments. The K-Nearest Neighbors (KNN) algorithm excels in recognizing patterns and categorizing flood stages based on historical data similarity. These ML approaches are valued for their interpretability, ease of use, and ability to integrate diverse data sources like rainfall, soil moisture, and streamflow measurements.

3.1.7 Limitations of Machine learning model

Although machine learning models—such as linear regression, support vector machines, K-nearest neighbors, decision trees, and random forests—provide strong data-driven capabilities for flood forecasting, they also come with notable limitations. These models typically demand large, high-quality, and well-annotated datasets for effective training, which may not be readily available in many flood-affected areas. They often function as black-box systems, offering limited transparency into the underlying physical processes, which can hinder acceptance by domain experts and decision-makers. Furthermore, ML models are prone to overfitting, particularly when handling complex inputs or insufficient training data. Their generalizability across different geographic regions or unobserved conditions is often weak, and they generally do not incorporate physical laws or hydrological principles unless deliberately combined with other methods. Consequently, purely ML-based models may face challenges in delivering accurate long-term predictions, ensuring physical consistency, or adapting in real-time without being integrated into hybrid or physically informed frameworks.

3.2. Deep Learning Models

Deep learning encompasses various types of models; each suited for specific tasks and data types. An urban flood data warehouse, comprising both structured and unstructured data, was developed, and a deep learning-based regression model was constructed to predict the depth of urban flooded areas [Wu et al., 2020]. DNN models offer a promising approach for creating accurate flood risk assessment maps, enhancing flood hazard management in the area [Pham et al., 2021]. The accuracy and efficiency of the spatial reduction and reconstruction approach and a deep learning framework are evaluated through its application to a real-world river system. [Zhou et al., 2021]. Fig 5 illustrates various types of Deep learning models.

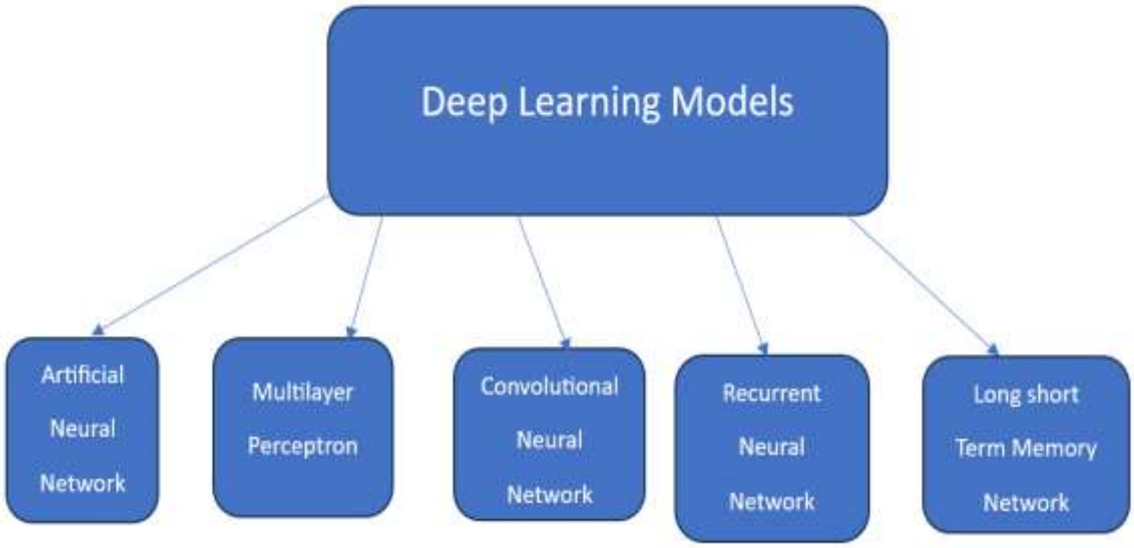


Fig 5: Different types of Deep Learning Models

3.2.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are a class of machine learning models inspired by the structure and functioning of the human brain. They consist of layers of interconnected nodes (neurons) that can learn complex patterns from data. Artificial Neural Networks (ANNs) serve as effective predictors of flood occurrences, even in regions characterized by predominantly microclimatic conditions [Dhunny et al., 2020]. ANN offers a dependable approach for identifying flood hazards in the River Nile [Mitra et al., 2016]. An embedded system combining IoT and machine learning demonstrates significant enhancement in predicting the probability of floods in a river basin [Dtissibe et al., 2020]. The Ensemble Artificial Neural Network model effectively predicted flooding, showing comparable or superior performance with short training datasets at appropriate time intervals compared to models using long training datasets [Dai et al., 2024]. A multi-layered artificial neural network, utilizing real-time monitoring sensors and systems, accurately predicted flood levels with minimal overall difference from actual levels across the tested dataset [Cruz et al., 2018].

3.2.2 Multilayer Perceptron

Multilayer perceptron is particularly useful for classification and regression tasks, including applications in areas like flood forecasting, where it can model the relationship between environmental variables and flood events. A Multilayer Perceptron (MLP) can serve as an effective algorithm for predicting flood events by utilizing rainfall time series data and water levels in a weir [Widiasari et al., 2017]. Feed-forward and recurrent multilayer perceptron have proven to be effective tools for flash flood forecasting [Darras et al., 2014]. An operational flood forecast model utilizing a Multilayer Perceptron Artificial Neural Network (MLP-ANN) is proposed for this catchment to provide short-term flood predictions [Valles, 2023]. A hybrid system combining neural networks and fuzzy logic is utilized for data partitioning, integrating specialist knowledge to develop intelligent solutions for river flow prediction [Fajardo-Toro et al., 2013]. The MLPNN algorithm, applied to monthly time series data of the Standardized Precipitation Evapotranspiration Index, can predict floods effectively [Ali & Hussain, 2017].

3.2.3 Convolutional Neural Network

They use convolutional layers to automatically extract features from input data. The CNN method demonstrates significant potential for real-time flood modelling and forecasting due to its simplicity, high performance, and computational efficiency [Kabir et al., 2020]. A flood susceptibility map can be developed using a deep CNN algorithm [Wang et al., 2020]. A two-dimensional (2D) Convolutional Neural Network (CNN) demonstrated higher accuracy in predicting flood peaks and arrival times, with lead times of 24 hours and 36 hours, respectively [Chen et al., 2021]. The CNN flood forecasting model, which incorporates hydrodynamics, flow routing, rainfall-runoff, and snowmelt processes, demonstrates higher accuracy in predicting past floods [Rao & Supraja, 2024].

3.2.4 Recurrent Neural Network

Specialized for sequential data where current inputs depend on previous inputs. They maintain a hidden state to capture information from previous time steps. A recurrent neural network is utilized to develop a real-time flood forecasting model, enabling accurate prediction of flood trends and peak occurrences during the flood period [Cai & Yu, 2022]. Recurrent neural networks demonstrated superior performance in both single-step and multi-step forecasting, making them a recommended tool for river flow prediction [Kumar et al., 2004]. Internal recurrent neural networks (IRNN) are employed for nonlinear system identification and are particularly effective for water flood assessment [Murariu et al., 2010].

3.2.5 Long Short-Term Memory Network

It is designed to overcome the vanishing gradient problem in traditional RNNs, enabling better learning of long-term dependencies. A local spatial sequential long short-term memory (LSTM) neural network effectively captures the attribution information of flood conditioning factors and the local spatial characteristics of flood data, while also possessing strong sequential modelling capabilities to address the spatial relationships of floods [Fang et al., 2021]. A hybrid approach integrates outputs from traditional physics-based models with historical data to train Long Short-Term Memory (LSTM) networks, enhancing flood forecasting by addressing computational efficiency and data scarcity challenges [Li et al., 2024]. LSTM processes river levels, rainfall data, and water discharge as inputs to predict flood or no-flood scenarios, demonstrating high accuracy in results [Kewat et al., 2022]. The LSTM model predicts peak flood arrival time with an absolute error of under 3 hours [Liu et al., 2023]. The Spatio-Temporal Attention LSTM model outperforms support vector machines (SVM), fully connected networks (FCN), and traditional LSTM models, demonstrating superior performance and high research value [Ding et al., 2019]. LSTM provided more accurate predictions of downstream water elevation levels compared to multiple linear regression models [Widiasari et al., 2018]. The Vector Direction -LSTM model integrates flood runoff vectorization with the LSTM neural network, enhancing the exploration of rising and receding water patterns, minimizing training gradient errors, and improving flood process simulation [Xie et al., 2024].

The table 4 provides a comparative summary of various deep learning-based flood forecasting models, evaluating them based on modelling type, input datasets, accuracy, computational requirements, lead time, and regional applicability to identify the best-performing model in each case.

Table 4: Studies based on deep learning

References	Modelling type	Input Dataset used	Accuracy	Computational Needs	Lead Time	Region	Best Performed Model
Lin Y.-B, & Lee, F.Z, 2021	R-CNN	Rainfall -Runoff	Very high	Very high	moderate	US	R CNN
Wajid M, & Abid M. K, 2024	LR ,DT, ANN	humidity, temperature, rainfall, waterflow	high	medium	fast	China	ANN
Puttinaovarat S, & Horkaew, P,2020	MLP	meteorological, hydrological, geospatial, crowdsource big data, Big Crowdsourced data	high	medium	moderate	Thailand	MLP
Dazzi, S, & Vacondio R, 2021	SVR, MLP, LSTM	Streamflow	high	high	Moderate	Italy	LSTM
Snehil & Goel, R,2020	GNBT, KNN	Flood damage data	moderate	Low	Fast	India	KNN
Praveen B, & Talukdar S. ,2020	ANN-MLP	Rainfall -Runoff	high	medium	moderate	India	ANN MLP
de Castro J. T, & Salistre, G,2013	ANN, LSTM, SVM, DT	Rainfall - Runoff, Stream flow	high	high	moderate	United States	LSTM
Sharma et al, 2022	ANN ,BN, RF	Rainfall -Runoff	high	high	moderate	India	ANN
Pham et al, 2021	DNN	hazard, exposure, vulnerability.	high	high	moderate	Vietnam	DNN
Zhou et al., 2021	LSTM	Streamflow	high	high	moderate	Australia	LSTM
Dhunny et al, 2020	ANN	Climatic Factors	moderate	medium	moderate	Mauritius	ANN
Mitra et al, 2016	ANN	Sensor data	moderate	medium	moderate	India	ANN
Dtissibe et al, 2020	MLP	Streamflow	moderate	medium	moderate	France	MLP
Dai et al, 2024	EANN	Streamflow	high	high	moderate	China	EANN
Cruz et al, 2018	MANN	Rain Gauge, Water Level, Soil Moisture Sensors	moderate	medium	moderate	Philippines	MANN

Widiasari et al, 2017	MR, MLP	Hydrological Data	moderate	medium	moderate	Indonesia	MLP
Darras et al, 2014	MLP	Streamflow	moderate	medium	moderate	France	MLP
Valles, 2023	MLP ANN	Rainfall-runoff	high	high	moderate	El Salvador	MLP ANN
Fajardo-Toro et al, 2013	Hybrid AI model	Streamflow	high	high	moderate	Colombia	Hybrid AI model
Ali & Hussain, 2017	MLPNN	Climatic Factors	moderate	medium	moderate	Pakistan	MLPNN
Kabir et al, 2020	SVR, CNN	hydrodynamic factors	high	high	moderate	UK	CNN
Wang et al, 2020	SVM, CNN	Historical Flood data	high	high	moderate	China	CNN
Chen et al, 2021	CNN	Streamflow	high	high	moderate	China	CNN
Rao & Supraja, 2024	CNN	hydrodynamics, flow routing, rainfall-runoff, snow melting	high	high	moderate	India	CNN
Cai & Yu, 2022	Hybrid RNN	Rainfall, Stream Flow	high	high	short	China	Hybrid RNN
Kumar et al, 2004	RNN	Streamflow	moderate	medium	short	India	RNN
Murariu et al, 2010	LSTM	Spatial Data	high	high	medium	China	LSTM
Li et al, 2024	LSTM	Historical and Physical data	high	high	medium	China	LSTM
Kewat et al, 2022	LSTM	River level, Rainfall data water discharge	high	high	medium	India	LSTM
Liu et al, 2023	RNN, GRU	Hydrological Data	high	medium	medium	China	RNN
Ding et al, 2019	SVM, FCN, LSTM, STALSTM	Precipitation, soil moisture, evaporation	Very high	Very high	short	China	STA LSTM
Widiasari et al, 2018	LSTM	Hydrological Data	high	high	medium	Indonesia	LSTM
Xie et al, 2024	VD LSTM	Hydrological Data	Very high	Very high	short	China	VD LSTM

3.2.6 Advantages of Deep Learning Model

In parallel, deep learning (DL) models have emerged as some of the most impactful advancements in flood forecasting, due to their strength in capturing temporal, spatial, and sequential patterns in data. Recurrent Neural Networks (RNNs) and their more advanced variant, Long Short-Term Memory (LSTM) networks, are particularly effective at handling time-series data such as precipitation and river discharge, making them ideal for dynamic flood prediction. Convolutional Neural Networks (CNNs), when applied to spatial datasets like satellite imagery or gridded rainfall, enhance capabilities in flood detection and mapping. Artificial Neural Networks (ANNs) and Multi-Layer Perceptrons (MLPs) continue to be widely used for their adaptability in modeling nonlinear systems, especially when combined with physical or statistical models. The emergence of hybrid frameworks—integrating ML/DL with traditional hydrological models—offers promising improvements in accuracy, reliability, and resilience. These advancements are driving the development of next-generation flood forecasting systems that are not only accurate and adaptive but also capable of real-time deployment across diverse environments.

3.2.7 Limitations of Deep Learning Model

Deep learning models—such as Artificial Neural Networks (ANN), Multilayer Perceptrons (MLP), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks—excel at modeling complex, nonlinear patterns in flood forecasting. However, they present several challenges. These models are highly data-dependent, requiring vast amounts of high-quality, high-resolution labeled data for effective training, which is often scarce, especially in under-monitored regions. Their black-box characteristics hinder interpretability, making it difficult to trace how predictions are formed—this can limit transparency and stakeholder confidence. Deep learning techniques are also computationally demanding, requiring substantial processing power and memory, particularly during the training phase. They are prone to overfitting, especially with limited or noisy datasets, and their ability to generalize to different locations or unseen flood scenarios is often limited. Furthermore, deep learning models do not inherently incorporate physical hydrological principles, necessitating hybrid approaches that combine them with domain knowledge to ensure realistic, reliable flood forecasting outcomes.

4. Analysis and Observation

Flood forecasting plays a vital role in disaster management and risk mitigation by helping to reduce damage to life and property. Over time, researchers have introduced a range of predictive models, from conventional hydrological approaches to cutting-edge machine learning and deep learning techniques. This review examines both traditional and contemporary flood forecasting methods, emphasizing their advantages, limitations, and emerging trends.

Traditional methods such as hydrological and statistical models form the foundation, while advanced techniques like hydrodynamic and groundwater models enhance predictive capabilities. Meteorological forecasting and river gauge data integration play critical roles in improving model reliability and early warning systems. Tools such as MIKE 11, Sobek, MODFLOW, and GSFLOW demonstrate the diversity and specialization of modeling techniques. Overall, combining these approaches provides a comprehensive framework for flood prediction and water resource management.

Modern flood forecasting methods have significantly advanced by integrating cutting-edge technologies, real-time data, and sophisticated modeling techniques. These innovations address the limitations of traditional approaches and enhance forecasting accuracy, extend prediction horizons, and provide timely early warnings for extreme flood events. The integration of modern technologies, such as IoT, cloud computing, and big data analytics, has transformed flood forecasting systems. Hybrid models that combine data-driven and physics-based approaches provide greater accuracy and robustness. Real-time monitoring and satellite remote sensing facilitate data acquisition in remote areas, improving forecasting reliability. Ensemble approaches address uncertainties effectively, enabling probabilistic flood forecasting. Social media and crowdsourcing are emerging as supplementary tools to enhance situational awareness and disaster response.

The referenced studies on flood forecasting predominantly utilize features such as rainfall-runoff data, hydrological data, stream flow, weather data, satellite data, sensor data, crowdsourced data, and crop damage. Among these, rainfall-runoff data constitutes the largest category at 33%, highlighting its critical role in flood prediction. Stream flow data closely follows at 32%, emphasizing the importance of water flow measurements in forecasting models. Hydrological data, accounting for 10%, includes parameters like water levels and soil moisture, which are essential for understanding watershed dynamics. Satellite data contributes 9%, offering valuable spatial insights, while sensor data adds 5%, providing on-ground observations. Weather data, at 4%, incorporates factors like temperature and humidity, and crowdsourced data, also at 4%, reflects the utility of citizen science in enriching datasets. Finally, crop damage data, representing 3%, is included to evaluate the socio-economic impacts of floods. Figure 6 further illustrates these dataset statistics, underscoring the dominance of rainfall-runoff and stream flow data in flood forecasting research.

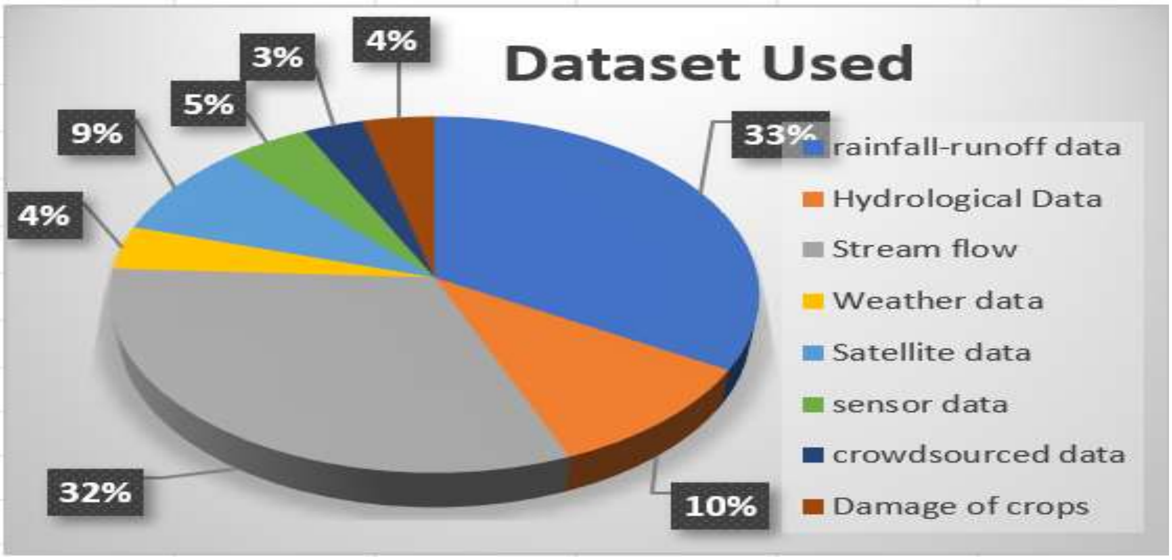


Fig 6: dataset statistics in Flood forecasting studies

Fig 7 presents the statistics of flood forecasting studies over various years, based on the referred studies. The graph titled "Flood Forecasting Studies" illustrates a significant increase in the number of studies conducted on flood forecasting over the period 1995 to 2024. Starting with a modest 3 studies in the 1995-2000 period, the number gradually increased to 4, 6, and 18 in the subsequent five-year intervals. However, a remarkable surge occurred between 2016 and 2020, with the number of studies reaching 45. This trend continued with another 48 studies conducted between 2021 and 2025, indicating a sustained high level of research activity in this field.

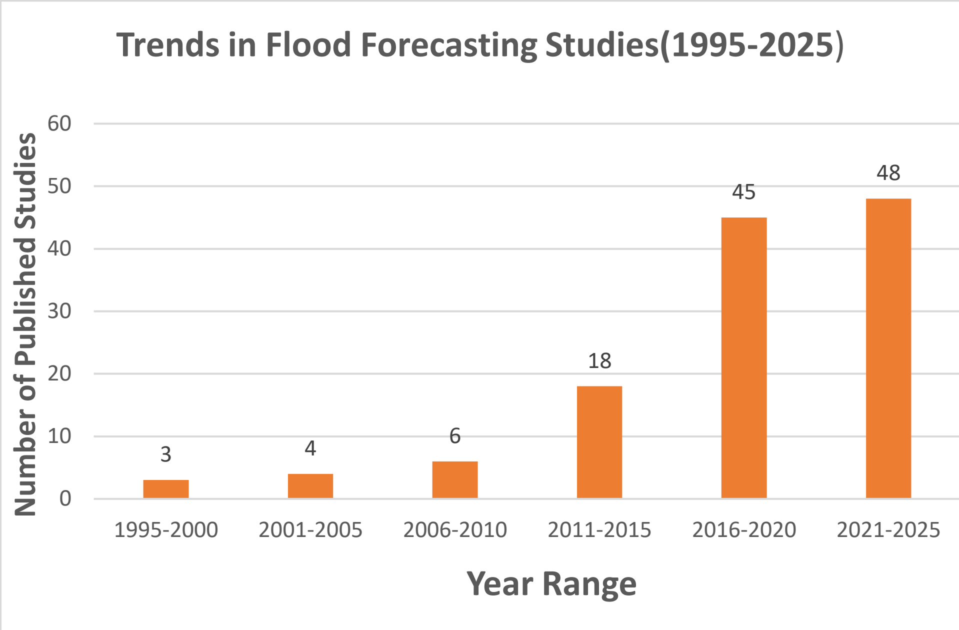
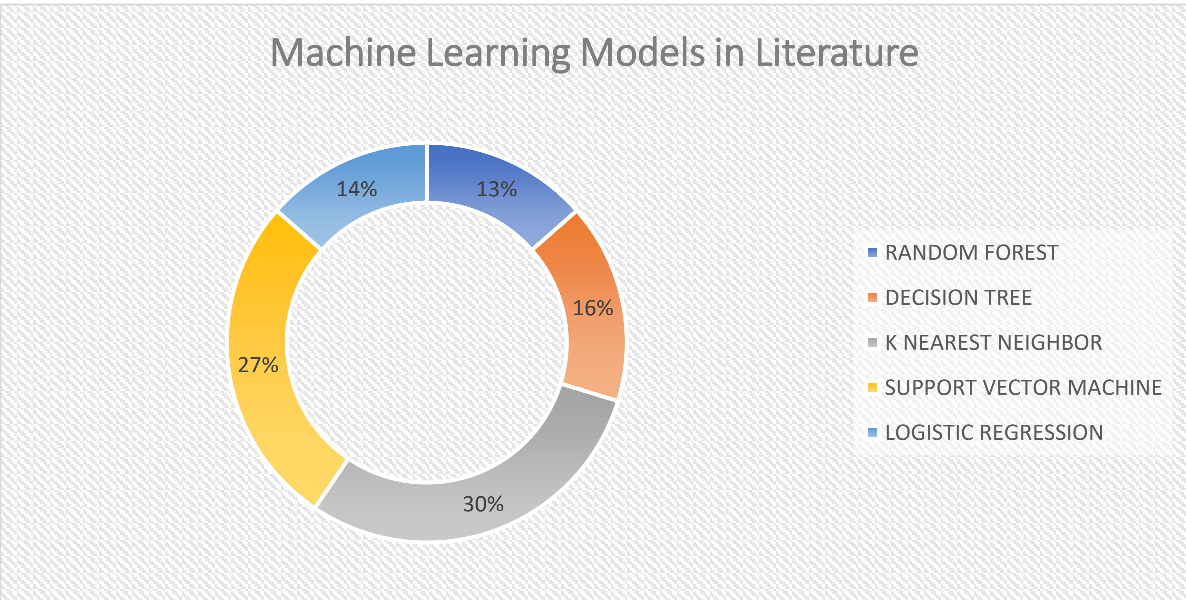


Fig 7: Statistics of Flood forecasting studies from 1995-2025

The fig 8 illustrates the statistics of machine learning models based on the number of studies conducted for each model. K-Nearest Neighbors is the most studied method among those listed. Random Forest and Decision Trees are comparatively less studied. Logistic Regression has the least studies at the beginning of the trend, but Support Vector Machine shows a rise before the peak.

Fig 8: Statistics of Machine learning Models in flood forecasting literature



A Fig 9 presents the statistical distribution of deep learning models based on the number of studies conducted for each model. Artificial Neural Networks (ANN) seem to dominate the study or application in this context, followed by Convolutional Neural Networks (CNN). Recurrent Neural Networks (RNN) and Multilayer Perceptron (MLP) have smaller shares, indicating fewer studies or applications. Long Short-Term Memory (LSTM) models have a moderate representation, likely due to their popularity in time-series or sequential data tasks.

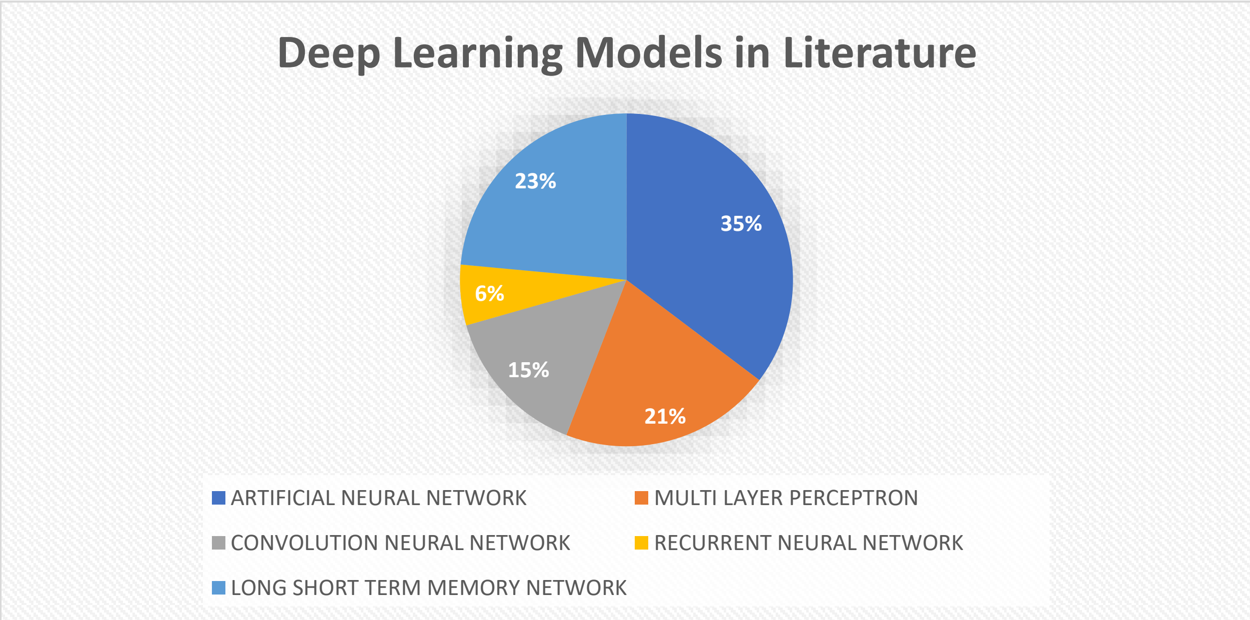


Fig 9: Statistics of Deep learning Models in flood forecasting literature

Fig 10 illustrates the prediction accuracy of various traditional flood forecasting models. Rainfall-Runoff Models and Groundwater-Based Models exhibit High accuracy, reflecting their effectiveness in capturing critical hydrological processes. River Gauge Data Models have medium accuracy, relying on real-time river level data. In contrast, Hydrodynamic Models**,** Statistical Methods**,** and Hydrological and Hydraulic Model**s** show Low accuracy, likely due to limitations in data requirements, assumptions, or dynamic adaptability. This chart underscores the varying reliability of these models and the potential need for integrating or advancing methodologies for better accuracy.

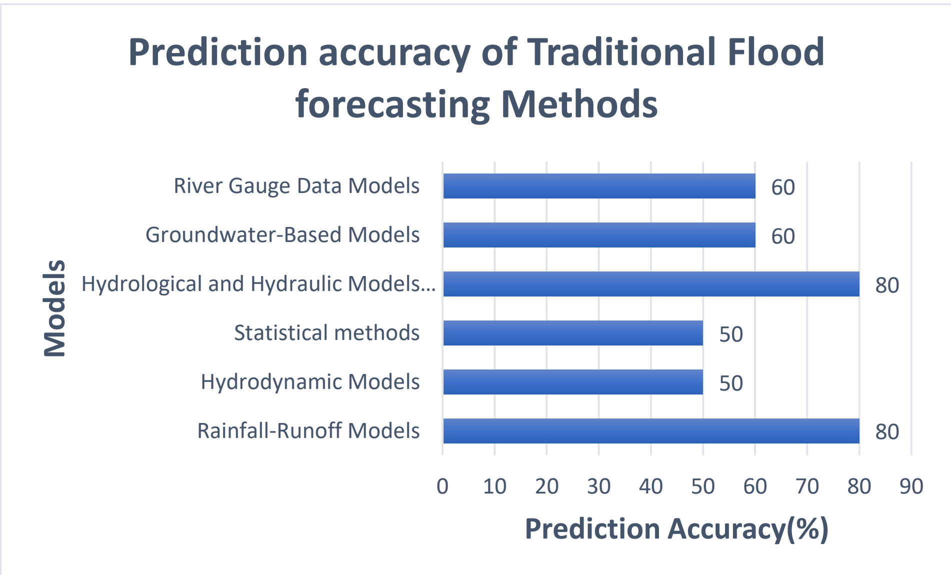


Fig 10: Prediction Accuracy of Traditional Flood Forecasting Models

Fig 11 illustrates the prediction accuracy of various modern flood forecasting methods, categorized into Low**,** Medium**,** High, and Very High levels. Deep Learning Models and Machine Learning Models demonstrate the highest accuracy (Very High), highlighting their advanced capabilities in handling complex data patterns. Hybrid Models and Ensemble Flood Forecasting achieve High accuracy due to their integrated approach. Methods like GIS and DEM**,** IoT and Sensors, and social media and Crowdsourcing are rated Medium, reflecting moderate reliability. Cloud Computing and Big Data Analytics and Numerical Weather Prediction also achieve medium accuracy, while Data Assimilation Techniques and Satellite Remote Sensing are rated Low, likely due to limitations in data availability or processing. This chart underscores the effectiveness of advanced computational techniques for improving flood prediction.

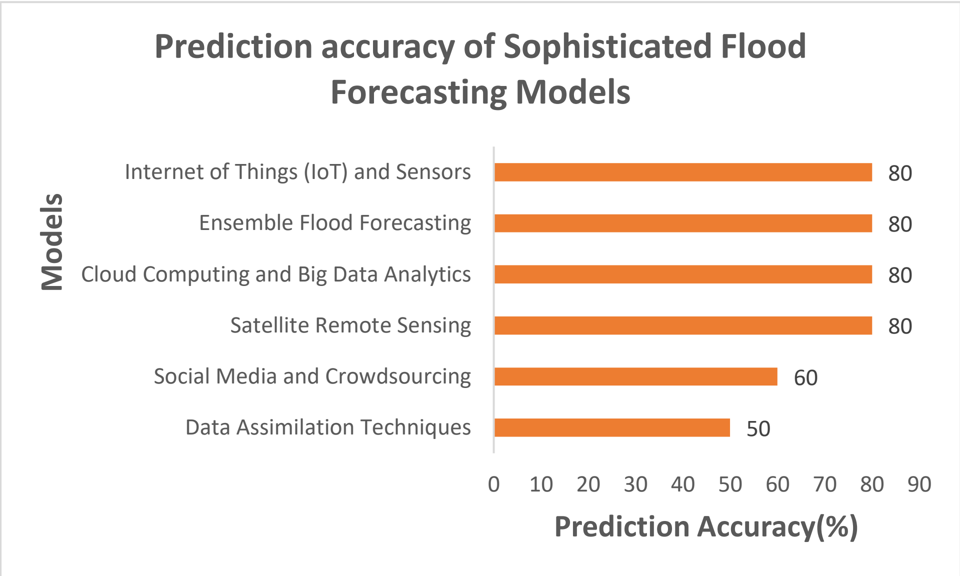


Fig 11: Prediction Accuracy of Sophisticated Flood Forecasting Models

Fig12 illustrates the distribution of flood forecasting studies across various countries, revealing a strong concentration in India, which leads with approximately 11 studies. The US follows with around 4 studies, while China and "Various Countries" each have roughly 6 and 3 studies respectively. All other listed countries, including regions in Africa, Australia, Greece, Bulgaria, Indonesia, the Philippines, Taiwan, Pakistan, Thailand, and Egypt, show significantly lower engagement in forecasting studies, with each registering 2 or fewer. This disparity highlights a potential focus on India, followed by the US and China, in this field of research.

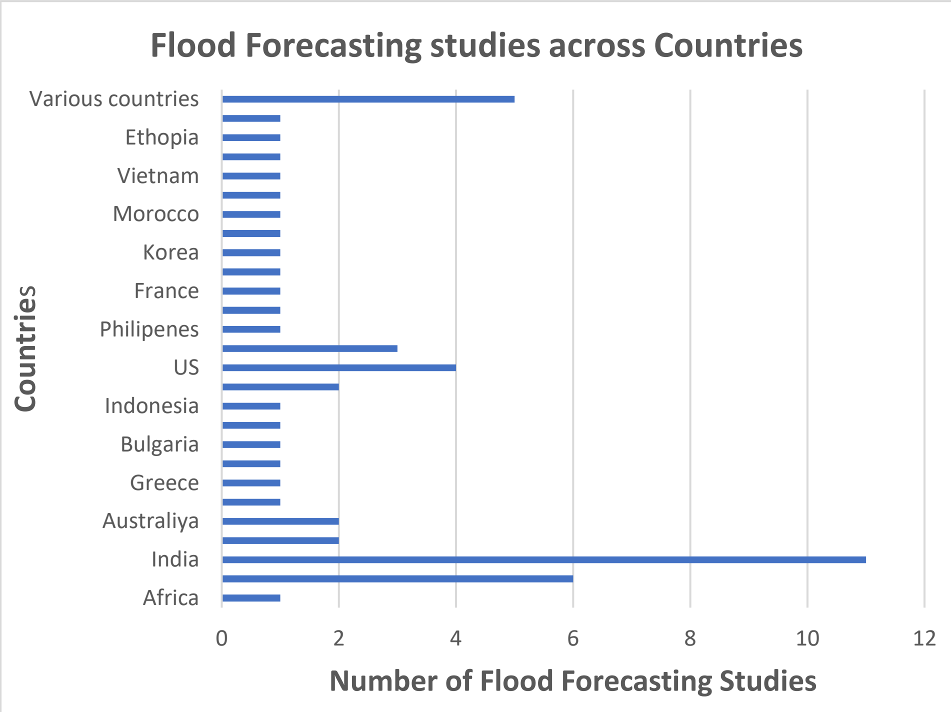


Fig12: Statistics of Flood forecasting studies across countries

The fig13 presents the number of research article publications focusing on flood forecasting with Machine Learning and Deep Learning across various nations. China leads with the highest number of publications, significantly surpassing all other countries. India holds the second-highest number, while the US, UK, France, Thailand, Indonesia, Taiwan, Netherlands, Bangladesh, Pakistan, and Australia all exhibit considerably lower publication counts. This disparity highlights a strong concentration of research output in China and, to a lesser extent, India in this specialized area of flood forecasting, suggesting a potential leadership role in advancing these techniques, while the remaining countries demonstrate comparatively less activity in terms of published research.

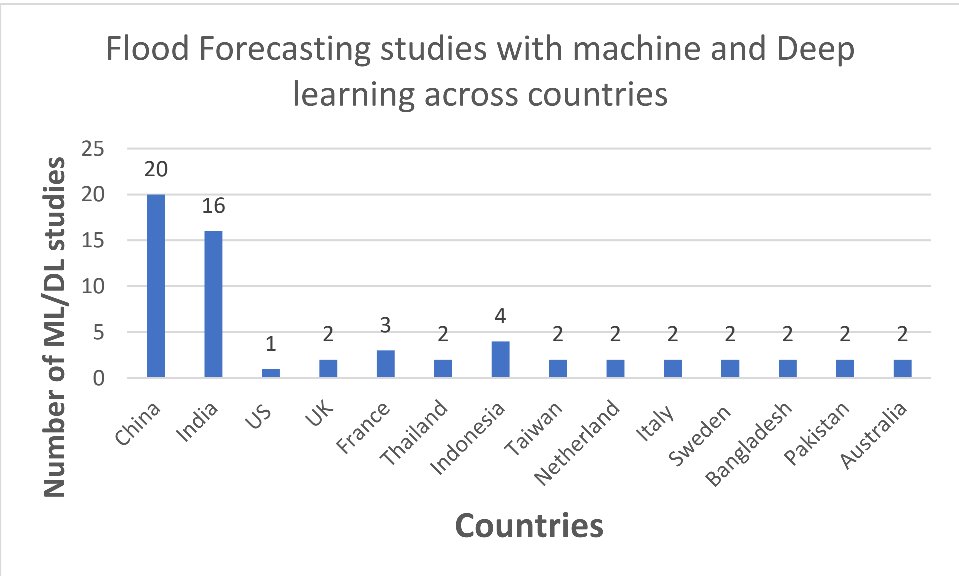


Fig 13: Flood forecasting with Machine and Deep Learning across nations

The comparison between traditional, sophisticated, and hybrid flood forecasting methods reveals distinct differences in their performance and operational needs. Traditional methods provide moderate to high accuracy with medium data requirements and lower resource demands, making them more feasible for areas with limited infrastructure. However, their real-time effectiveness and adaptability to different regions are only moderate. Sophisticated methods, such as those using machine learning and deep learning, offer improved accuracy and real-time capabilities but require large datasets and significant computational power. Hybrid models, which combine traditional and modern techniques, deliver the highest levels of accuracy, real-time applicability, and adaptability across regions. Despite these advantages, they come with very high data demands, require advanced computational systems, and depend on specialized technical knowledge making them most suitable for regions with robust forecasting infrastructure.

Traditional flood forecasting methods, including statistical and hydrological models, provide moderate to high accuracy, rely on medium levels of data, and are generally suitable for regions with limited technical resources. In contrast, sophisticated techniques deliver higher accuracy and better real-time performance but require large datasets and significant computational capabilities. Hybrid models, which combine physical and data driven approaches, achieve the highest accuracy and adaptability, though they demand extensive data and substantial resources.

Criteria	Traditional Methods	Sophisticated Methods	Hybrid Models
Accuracy	Moderate to high	High	Very High
Data requirement	Medium	High	Very High
Real time applicability	Moderate	High	Very High
Resource need	Low to Medium	High	Very High
Regional Adaptability	Moderate	High	Very High

Fig 14: comparative matrix showing Traditional vs. Sophisticated vs. Hybrid methods

5.Research Gaps and Future Directions

Although hybrid models have gained prominence in flood forecasting, several critical gaps remain. A key challenge lies in the absence of standardized frameworks for integrating diverse modeling approaches such as combining data-driven techniques with physics-based or statistical models which often leads to inconsistent performance and limited reproducibility. Most existing hybrid models are calibrated using region-specific datasets, reducing their applicability across varied hydrological and climatic zones. Moreover, determining the optimal trade-off between model complexity and computational efficiency especially for real-time forecasting remains unresolved. Other issues include limited interoperability among datasets, the scarcity of high-resolution, multi-source data, and inadequate incorporation of dynamic uncertainties such as those arising from climate change, evolving land use, and socio-economic transformations. These limitations restrict the overall robustness, transferability, and adaptability of hybrid models.

Advancing hybrid modeling in flood forecasting calls for the creation of integrated frameworks that support the seamless fusion of multiple modeling techniques, ideally built on interoperable data standards and opensource infrastructure. There is also a growing need to develop interpretable and explainable hybrid models by embedding transparent AI methods alongside established physical modeling approaches to build stakeholder confidence. To enhance real time forecasting potential, future models should leverage emerging technologies like edge computing, federated learning, and lightweight architectures to reduce latency and computational demands. Modular model designs that allow adaptive updates in response to incoming data or environmental changes will be essential. Additionally, incorporating innovations such as synthetic data generation, transfer learning, and multi objective optimization will boost generalizability and resilience, making hybrid models more effective across diverse flood-prone regions facing uncertain future conditions.

6. Conclusion

This review illustrates the progression of flood forecasting methodologies from conventional hydrological and statistical models to advanced machine learning (ML) and deep learning (DL) techniques. While traditional approaches have laid the groundwork for flood prediction, they often fall short in capturing the complex, nonlinear, and spatiotemporal dynamics of flood events. In contrast, ML and DL models such as Random Forest, Support Vector Machines (SVM), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) offer improved accuracy by leveraging large datasets and sophisticated algorithms. However, these models can be prone to overfitting and may lack transparency. Hybrid models, which integrate physical knowledge with data-driven techniques, represent a highly promising direction. By combining strengths from both domains, they improve feature extraction, enhance generalizability, support real-time forecasting, and adapt effectively to varied hydrological settings.

Despite these developments, important research gaps persist. Limited data availability, especially in low resource regions, remains a major constraint. Furthermore, the absence of standardized evaluation frameworks across different geographic and climatic contexts hinders model comparison and validation. Real-time operational use and integration with early warning systems are still in early stages, and the black-box nature of many AI-driven models continues to present challenges for interpretability and stakeholder confidence.

To bridge these gaps, policymakers should prioritize investment in open-access hydrometeorological data systems and promote the adoption of AI-enhanced models within official forecasting and disaster management frameworks. Researchers should focus on developing robust, interpretable, and data-efficient hybrid models that leverage remote sensing, IoT technologies, and real-time data assimilation. A collaborative, interdisciplinary effort encompassing hydrology, data science, and environmental policy is essential to advance flood forecasting systems that are accurate, scalable, and resilient in the face of evolving climate challenges.

Author's contribution statement

Reena. S: Writing – original draft.
Harikrishnan. D: Supervision, Writing – review and editing.
Salaji. S- Supervision, Writing – review and editing.

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Conflicts of interest

The authors have no conflicts of interest to declare.

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