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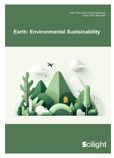

Review

Data-Driven Innovations in Flood Hazard Assessment with Machine Learning

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Abstract: Floods, as natural disasters, have a profound impact on society. Assessing them is highly complex due to the interplay of factors such as meteorology, topography, and land cover. Accurate forecasting is essential to reduce disaster risks, guide emergency response strategies, and minimize economic and social losses. Recent advancements in machine learning have significantly improved the accuracy of flood predictions, offered more cost-effective solutions and enhanced decision-making processes. This paper reviews the most common and recent advancements in machine learning applications for flood hazard assessment and forecasting and compares their performance with traditional approaches such as numerical modelling and remote sensing. While numerical models provide detailed predictions, they are computationally demanding and depend on precise data inputs. While remote sensing provides valuable large-scale data for flood monitoring, it often faces limitations in real-time responsiveness and accuracy, particularly under rapidly changing flood conditions. Machine learning addresses these limitations by leveraging historical data to identify patterns and refine predictions, improving both accuracy and efficiency. Challenges such as the variability of model performance across different regions and the requirement for high-quality data remain. This paper explores both long-term and short-term flood forecasting and the hazard assessment, shows that combining different methods in hybrid models can improve accuracy by reducing data uncertainties. Future research should prioritize refining machine learning algorithms for diverse environments, improving data processing techniques, and developing integrated methodologies. These advancements will lead to more reliable flood predictions, ultimately helping to mitigate the risks and impacts of flood disasters.

Keywords: machine learning; flood hazard assessment; model optimization; forecasting

1. Introduction

Floods are among the most frequent and devastating natural disasters, posing significant threats to human life, infrastructure, and socio-economic stability. Flood forecasting, a vital non-structural measure for flood control and disaster mitigation, plays a crucial role in providing accurate and timely predictions of flood events [1]. It remains a central focus—and a persistent challenge—in hydrology, as the development of reliable real-time forecasting models is one of the most demanding tasks in the field.

The destructive force of floods can cause extensive damage to vehicles, public utilities, and critical infrastructure, requiring substantial financial resources and prolonged recovery efforts. Disruptions to transportation and communication networks further hinder societal functions and impede emergency response operations [2]. In addition, floods have severe impacts on agriculture and the environment, triggering widespread soil erosion, destruction of vegetation, and disruption of natural habitats. These effects reduce soil fertility, destroy wildlife ecosystems, and contribute to biodiversity loss, ultimately threatening ecological balance and environmental health [3]. Moreover, floods often result in significant water pollution due to the failure of sewage treatment facilities, allowing untreated industrial and domestic wastewater to contaminate rivers, lakes, and other water bodies. This contamination not only endangers aquatic ecosystems but also compromises the safety of drinking water supplies, increasing the risk of waterborne diseases such as cholera and typhoid fever [4].

In recent decades, the frequency and intensity of flood events have risen markedly, primarily due to accelerating global climate change. The growing likelihood of extreme and catastrophic events, coupled with increasing uncertainty in their spatial and temporal distribution, underscores the urgent need for improved flood prediction and management strategies [5]. Enhancing the accuracy of flood forecasting, extending lead times, and advancing flood risk mitigation through innovative theories and technologies have become pressing priorities in the earth and environmental sciences.

Despite these needs, the practical application of flood damage models remains limited due to the complex nature of flood events and challenges in acquiring high-resolution loss data [6]. Major obstacles include the lack of comprehensive damage records, uncertainties in loss estimation, frequent omission of indirect and intangible impacts, and difficulties in transferring models across diverse regions and contexts [7]. These challenges continue to hinder the development of robust, transferable flood damage models.

Flood forecasting forms the foundation of disaster impact assessment by estimating the timing, magnitude, and spatial extent of flood events. This information provides critical input for identifying affected areas and quantifying potential impacts. In this context, machine learning (ML) approaches have emerged as powerful tools for flood hazard assessment, particularly in real-time forecasting [8]. By utilizing historical datasets, ML models can capture complex, nonlinear relationships between flood flows or water levels and various influencing factors, thereby enhancing predictive accuracy through data-driven optimization. Their scalability and computational efficiency have generated growing interest within the research community. However, the effective deployment of ML models is often constrained by the limited availability of high-quality training and validation data—a persistent issue in flood hazard modeling [9]. Furthermore, uncertainties in both input data and model architecture can propagate through the forecasting process, amplifying overall prediction uncertainty. Despite recent advances, comprehensive frameworks for quantifying and managing these uncertainties remain underdeveloped.

This article presents a critical review of recent and widely used machine learning models for flood hazard assessment, including traditional algorithms, deep learning techniques, and hybrid modeling approaches. It also provides a systematic review of ML-based flood hazard assessment studies conducted between 2019 and 2024. It also identifies the key challenge of quantifying climate change impacts on flood risk and forecasting. Drawing upon the extensive body of research and practical experience in flood modelling, this review highlights the distinctive features of these models, examines current optimization strategies, and discusses future directions for research. The insights presented aim to inform and guide ongoing efforts to advance flood forecasting and risk management within the broader context of Earth and Environmental Science. Although this review focuses on recent advancements (2019–2024), it also references several earlier pioneering studies in machine learning-based flood modeling to provide historical context and continuity.

2. Flood Hazard Assessment in Flood Forecasting

Flood hazard assessment, particularly in forecasting, plays a vital role in natural hazard management. Over time, it has evolved from early frequency analysis techniques to sophisticated model simulations and hybrid approaches. The origins of flood forecasting date back to the early 20th century, motivated by the need for flood discharge estimation and management in large reservoirs [10]. This prompted the development of hydrological statistical tools such as the annual maximum peak discharge, annual exceedance probability (AEP), and recurrence interval, which remain fundamental for predicting flood probabilities and designing effective flood control measures.

Extreme value analysis in flood studies typically employs two primary approaches: (1) flood frequency analysis based on observed streamflow records, and (2) the combination of design rainfall data with watershed models to simulate flood events. Various statistical distribution functions including standard, lognormal, Gumbel, and log-Pearson types are applied to characterize the statistical behaviour of extreme flood events [11].

The development of hydrological models has significantly enhanced flood forecasting capabilities. Early models were often constrained in their ability to simulate hydrological processes across diverse geological conditions. In response, distributed watershed models emerged, subdividing catchments into hydrologically homogeneous units to improve simulation accuracy. The integration of Geographic Information System (GIS) and remote sensing technologies has further strengthened model calibration and parameter estimation, especially in data-scarce regions [12]. Forecasting models have progressed from one-dimensional systems for example Hydrologic Engineering Center's River Analysis System (HEC-RAS) and DHI-MIKE11 （Danish Hydraulic Institute） to more advanced two-dimensional and three-dimensional models [13]. While 2D models improve representation of lateral floodplain flow, 3D models offer high-resolution simulations by solving the full Navier-Stokes equations, albeit at the cost of significantly greater data and computational requirements [14].

Flood risk assessment seeks to evaluate the likelihood and consequences of flood events, considering both their spatial distribution and underlying drivers. This process encompasses risk identification, quantification, and analysis, integrating hazard, exposure, and vulnerability components. The effectiveness of any assessment approach depends on the spatial resolution and completeness of input data, which in turn influences both the accuracy and timeliness of the results [15]. Current flood risk assessment methods can be broadly classified into five categories: historical hazard analysis, multi-criteria indicator frameworks, remote sensing and GIS-based integration, scenario-based simulations, and machine learning approaches [16]. This paper focuses on the latter machine learning methods, highlighting their current development, practical advantages, and inherent limitations.

3. Machine Learning Assisted Assessment Methods

3.1. General Concepts

ML is a data-driven approach that identifies patterns in large datasets to support predictive tasks. While traditional ML models have provided a foundation for various applications, they often struggle with modeling complex, high-dimensional functions due to their relatively simple architectures and computational constraints [17], which limits their effectiveness in tasks such as flood forecasting. Historically, urban flood simulation has relied on computationally intensive physics-based models. In contrast, data-driven ML methods offer greater efficiency and cost-effectiveness, though maintaining a balance between model complexity and predictive accuracy remains a significant challenge [18].

ML-based flood modeling typically involves several key stages: data acquisition, preprocessing, model training, optimization, and validation. Traditional ML models are computationally efficient and relatively easy to implement but are limited in their ability to capture complex nonlinear relationships and extract deep features from data [19]. Deep learning (DL) models, characterized by multiple hidden layers, are capable of capturing intricate patterns and complex dependencies [20]. However, these models require large datasets and significant computational resources, which can hinder their scalability, especially in data-scarce environments.

To address these limitations, hybrid approaches that integrate traditional ML techniques with deep learning frameworks have emerged. These methods can enhance performance while mitigating the computational burden associated with purely deep models [21]. Future research will likely focus on improving data efficiency, enhancing model generalization, and developing novel hybrid architectures that can adapt to diverse flood prediction scenarios.

Compared to traditional statistical models—which often rely on manual feature engineering and rigid assumptions—ML approaches provide greater flexibility. They can automatically uncover latent features and nonlinear interactions, thereby reducing bias and improving performance [22]. Nevertheless, ML models face persistent challenges, including overfitting, high computational demands, and interpretability issues [23]. Techniques such as transfer learning and the incorporation of alternative data sources can partially address these limitations [24].

Improving model interpretability, ensuring data quality, and enhancing computational efficiency are critical for advancing flood forecasting capabilities. The development of robust hybrid models, along with transparent algorithms and refined data management strategies, is essential to harness the full potential of ML in disaster prevention and emergency management [25]. A key advantage of ML models lies in their adaptability: unlike traditional models that require full retraining, ML models can update incrementally as new data becomes available [26]. This dynamic learning capability is especially valuable for flood forecasting, where environmental conditions can change rapidly.

Moreover, ML models can efficiently handle high-dimensional and unstructured data without extensive manual preprocessing, thanks to their ability to automatically extract informative features [27]. Their strong generalization capabilities allow the application of learned representations to new and unseen scenarios, resulting in more reliable predictions compared to traditional methods [28]. However, deep learning models in particular remain "black boxes" to many users, raising concerns about transparency and interpretability [29]. Recent advances, such as model-agnostic interpretation techniques, are helping to bridge this gap. Nonetheless, interpretability remains crucial in operational contexts like flood forecasting, where stakeholders require understandable and justifiable predictions [30].

Overfitting also poses a significant risk when models are trained on limited or biased datasets. To ensure robust generalization, regularization techniques and careful hyperparameter tuning are essential [31].

When evaluating the suitability of ML models for flood prediction, it is important to systematically assess their strengths and limitations. Different model types vary significantly in terms of data requirements, computational efficiency, predictive accuracy, and interpretability [32]. To facilitate this assessment, Table 1 presents a strengths-and-weaknesses matrix that compares traditional ML models. This matrix provides researchers and practitioners with a structured reference framework, enabling a more informed selection of models based on application-specific needs. By analyzing these characteristics, the applicability of various models across different flood prediction scenarios can be better understood and leveraged effectively.

Table 1. Strength and weakness matrix for machine learning models.

Machine Learning Model	Strength	Weakness	Reference
Linear Regression	Fast training speed; low cost; Effective for linearly separable data.	Only use to handle linear relationships.	[33]
Decision Tree	Requires minimal data preprocessing; Dealing with both classification and regression problems.	Prone to overfitting; have problem when deal with continuous numerical features.	[34]
Random Forest	Reduce overfitting problem; Robust; Suitable for large database.	High model complexity; Slow straining speed; Not suitable for high-dimension dataset	[35]
Support Vector Machine	Suitable for high-dimension dataset; Suitable for both linear and non-linear classification problem.	Long training time; Need has data normalization and preprocessing.	[36]
K-Nearest Neighbors	Suitable for small sample datasets. No need training phase; Suitable for non-linear relationship.	High cost; Sensitive to data scale and dimensionality; Sensitive to noisy data.	[37]
Neural Networks	Automatically learns complex patterns and non-linear relationships from data; Suitable for image.	High model complexity; Long training time; Poor interpretability.	[38]
Long Short-Term Memory	Suitable for learning complex patterns.	High model complexity; Long training time; Poor interpretability.	[39]

To enhance the reliability and applicability of machine learning in flood forecasting, greater emphasis should be placed on developing more interpretable models and improving regularization methods. Tackling the challenges of computational demand, model transparency, and overfitting will be crucial for broader adoption and practical effectiveness. Hybrid approaches that integrate the strengths of both traditional and machine learning models may offer a balanced solution, overcoming individual limitations while maximizing their combined advantages [40].

In the field of flood forecasting, a wide range of machine learning models has been extensively employed to improve the accuracy and timeliness of predictions. These models include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests (RF), Probabilistic Neural Networks (PNN), Long Short-Term Memory networks (LSTM), and the Adaptive Group Method of Data Handling (AGMDH) [41]. Each model offers distinct characteristics and advantages. For example, ANN can capture complex nonlinear relationships between input and output variables to deliver high-precision forecasts [42]. SVM constructs optimal hyperplanes to separate data classes effectively, while RF enhances predictive accuracy and robustness by aggregating multiple decision trees. PNN leverages probabilistic approaches for classification and regression tasks. LSTM, a specialized form of recurrent neural network, is particularly adept at modeling long-term temporal dependencies in time-series data [43]. ASGMDH further contributes to predictive performance by employing polynomial fitting and adaptive optimization strategies to improve model generalization [44]. The application of these models in flood forecasting not only enhances prediction accuracy but also provides vital support for real-time flood warnings and disaster response planning. Table 2 summarizes previous studies of machine learning models used in flood forecasting.

Table 2. Review of machine learning models in flood forecasting.

Modeling Technique	Novelty	Objective	Accuracy	Reference
Trained ANN	Square error calculation; definition of partial derivatives; change in synapse weights	Achieving highly accurate long-term forecasts	The average prediction error for 10 days was 50.96 cm. At the same time, the differences relative to other models ranged from 49.22% to 78.98%	[45]
Boosting-ANN	The base learning algorithm generates new weak prediction rules	Improving the accuracy of the model	RMSE (0.19), MAPE (2.72) and lowest MAE (0.15), NSE (0.99)	[46]
ANN	The momentum equation in the SWE local inertia approximation is replaced with two data-driven methods (curve fitting and artificial neural networks)	Reduced runtime of diving equations and improved generalization for real-time flood prediction.	The simulation speed of the local inertia model is improved by 23%.	[47]
RF	Water depths for the six sections of the RF alternative model and TUFLOW model	Improved capacity for real-time street-scale flood warning for urban coastal communities to address urgent flood nuisance issues	MSE is 3.2×10^{-6}	[48]
SVR&PNN	The databases used to train SVR and SOM were constructed from 1D and 2D flood analyses	Simultaneous prediction of rainfall returns periods and observation of rainfall inundation maps	The highest fit of the predicted flood map for the study area was 85.94 per cent	[49]
SVM	Two SVM using a numerical model as data producer, were developed to forecast the flood alert and maximum flood depth	Enabling real-time flood forecasting	RMSE and MBE are below 0.05, PR and TPRH are above 90%, and CE and CC are above 0.9 for SVM model	[50]
Advanced LTSM ASGMDH	The new polynomial scheme in ASGMDH allows for the inclusion of second and third order polynomials with two or three different inputs in each polynomial	Creating four different types of models that allow for a more comprehensive representation of the underlying relationships between variables.	About 20% of all forecast samples had relative errors of less than 1%, while 38% of the samples had relative errors of less than 2%.	[51]

Although traditional two-dimensional hydrodynamic models offer high accuracy, their long simulation runtimes hinder real-time flood prediction applications. To address this, researchers proposed a hybrid approach that replaces computationally expensive components of fluid dynamics simulations with data-driven approximations [40]. Two methods were evaluated: integrated curve fitting and ANN-based models applied to finite volume schemes solving the local inertia form of the shallow water equation (SWE). Results demonstrated that ANNs trained on randomly sampled datasets yielded higher accuracy than those trained on simulation outputs. Moreover, the curve-fitting approach exhibited superior generalization and improved simulation speed by 23%.

Researchers have introduced a novel system, termed ‘Flood 2.0’ [45], which integrates a proprietary machine learning library and a flood-area visualization module to enhance the accuracy of long-term flood forecasting. The machine learning library comprises two core components: data preprocessing and prediction. In the preprocessing phase, the study employs PNNs to establish data filtering rules that automatically generate high-quality initial datasets while removing extraneous noise. In the subsequent prediction phase, a Recurrent Neural Network (RNN) is utilized to forecast water levels based on the refined data. Following ten days of predictive experiments, results demonstrate that the Flood 2.0 system significantly outperforms existing models, achieving improvements in prediction accuracy ranging from 49.22% to 78.98% [45]. These findings underscore the effectiveness of the system’s mathematical and technical innovations.

In a recent study, researchers applied various preprocessing techniques—including Variational Mode Decomposition (VMD), Bagging, Boosting, and hybrid methods such as Bagging-VMD and Boosting-VMD—to daily rainfall data from Malaysia’s Long Canal Basin. These preprocessing methods were integrated with ANN and SVR to improve prediction performance [46]. Among these, the combination of Boosting-VMD with SVR and ANN produced the best results, significantly outperforming baseline models.

Simultaneously predicting rainfall recurrence periods and generating inundation maps is valuable for real-time flood response. Researchers used PNN and SVR to estimate rainfall recurrence intervals and predict flood volumes and inundation maps [49]. The results showed a high fitting degree of 85.94% for expected flood maps, demonstrating the practicality of the proposed method in improving urban flood response capabilities.

For urban flood forecasting, researchers developed two SVM models to predict flood warnings and maximum flood depths. These models integrated numerical simulations from MIKE FLOOD with SVM-based predictions, resulting in highly accurate and rapid forecasts. Notably, the SVM model delivered results in just 2.1 milliseconds, compared to 25 h required by the numerical model, demonstrating a significant improvement in computational efficiency [50].

In the context of urban flood prediction, physics-based models are often computationally intensive and time-prohibitive. To overcome this challenge, the study investigated the use of the RF machine learning algorithm as a faster alternative [51]. The RF model was trained to relate terrain and environmental features to hourly water depth data derived from high-resolution physical simulations. The results revealed that the RF model reduced computation time by a factor of 3000, significantly enhancing the feasibility of real-time decision support systems. In a related study, the Adaptive Structural Data Processing Group Method was introduced for daily river flow prediction, incorporating historical flow records alongside real-time temperature and precipitation data. The simplest model, using maximum temperature, precipitation, and historical flow, achieved high accuracy with an R^2 value of 0.985 during training and 0.992 during testing. The ASGMDH model demonstrated high reliability and practical potential, with a relative error of less than 15% for many samples.

Accurate prediction of river water levels is critical for effective flood control planning and floodplain management. Achieving high predictive accuracy often requires more than raw rainfall inputs and standard machine learning regression techniques [52]. Preprocessing methods play a vital role in enhancing data quality before applying predictive models.

Machine learning is widely used to develop empirical models within the framework of data-driven modelling. This approach effectively addresses challenges such as system complexity by complementing gaps in scientific understanding with models derived directly from data [53]. Compared to traditional simulations, machine learning models are typically more cost-effective in terms of computational resources [54]. Moreover, they are particularly well-suited for refining or post-processing predictions from physics-based models, enabling better alignment with specific local conditions.

3.2. Uncertainty in Flood Hazard Assessment

3.2.1. Input Uncertainty

Uncertainty quantification remains a significant and widely acknowledged challenge in climate science, necessitating the integration of multiple emission scenarios and climate models to generate reliable near-term projections [55]. However, recent research suggests that fully specified probability distributions accounting for all sources of uncertainty may not be essential for effective climate risk assessment [56]. Instead, a discrete, scenario-based approach purposefully structured to capture high-impact, low-probability events, which provides a practical and complementary alternative framework [57]. Numerical simulations demand high precision and comprehensive, high-quality datasets to ensure reliable outcomes. Their effectiveness depends critically on the integration of extensive hydrological, meteorological, and topographic information [58]. However, discrepancies in data accuracy, measurement errors, and inconsistencies can introduce significant uncertainties [59]. Variations in hydrological data intervals, meteorological coverage, and terrain resolution, for instance, can markedly influence model performance [60]. Rigorous quality control and consistency across datasets are therefore essential for the success of numerical simulations.

Accurate flood prediction relies on high-resolution spatiotemporal inputs, encompassing meteorological, hydrological, topographic, and land use data [61]. However, these datasets are often constrained by limited availability, missing values, and significant noise, which can compromise prediction accuracy [62]. Addressing these data quality issues may require the integration of supplementary data sources and the implementation of targeted quality enhancement strategies.

In areas with limited ground-based observations, satellite and remote sensing products are increasingly employed to offer broad-scale insights into flood events [63]. Despite their growing use, these data sources present notable limitations, such as coarse spatial resolution, data gaps due to cloud cover, and difficulties in integrating heterogeneous datasets [64]. Moreover, intrinsic errors and biases in remote sensing data necessitate rigorous correction and validation procedures [65].

While recent technological advancements such as improved sensor resolution and increased observation frequency are enhancing the spatiotemporal granularity of available data [66], further progress in algorithm development is essential to fully exploit these resources for reliable and timely flood forecasting [67].

The distinct data requirements of numerical simulation, machine learning, and remote sensing highlight the inherent strengths and limitations of each approach [68]. Numerical simulations offer high precision but are constrained by the need for exhaustive and accurate datasets. Machine learning approaches are more adaptable to varying data availability but remain vulnerable to errors embedded in historical records. Remote sensing methods introduce further complexities associated with resolution variability and processing artifacts, necessitating thorough validation [69]. Variations in hydrological data intervals, meteorological coverage, and terrain resolution, for instance, can markedly influence model performance. Rigorous quality control and consistency across datasets are therefore essential for the success of numerical simulations [70]. Machine learning methods, while typically less demanding in terms of data volume, similarly require high data completeness and accuracy. These models infer predictive patterns from historical data, rendering them highly sensitive to missing, noisy, or erroneous inputs [71]. In flood forecasting applications, inaccuracies in statistical features or historical trends can propagate through models and significantly impair predictive performance.

Integrated ML frameworks hold significant potential for improving the accuracy of flood prediction. One notable study proposed a probabilistic two-stage approach that combines decision trees and ANNs to process satellite imagery for estimating flood probabilities [72]. This methodology proved effective in mitigating urban drainage inundation risks, as demonstrated in the case of Kaohsiung City. In parallel, an ANN-based predictive system, validated using upstream discharge data from Sudan's Dongola Nile River station, demonstrated operational reliability for real-time flood hazard detection [73]. These developments illustrate how ML architectures enable the synergistic integration of diverse data sources including meteorological observations, remote sensing products, and historical datasets to deliver superior forecasting performance [74].

To address challenges related to data scarcity and uncertainty in hydrological modelling, researchers have proposed a novel synthetic data generation strategy based on Generative Adversarial Networks (GANs) [75]. Although still emerging within the field of hydrology, this approach offers promising potential to enhance data availability and improve model robustness.

Mitigating the effects of input uncertainty on flood risk assessment has also become a focal point. Data preprocessing plays a critical role in enhancing input quality. Techniques such as data cleaning, interpolation, and fusion reduce errors and uncertainties, while multi-source data fusion—integrating satellite remote sensing, ground observations, and GIS data overcomes the limitations of individual sources and improves overall data reliability and representativeness [76]. Effective preprocessing is essential for improving ML model performance [77], particularly in hydrological applications where predictive accuracy is vital for sustainable water resource management and environmental forecasting [78]. Key preprocessing practices include data normalization, handling of missing values [79], and feature selection [80], which collectively improve dataset integrity and optimize model training [81]. These methods help transform raw inputs into more model-suitable formats, thereby enhancing predictive capability in complex hydrological contexts [82].

Furthermore, uncertainty quantification and propagation techniques such as Monte Carlo simulations and Latin Hypercube Sampling are instrumental in evaluating how input uncertainties influence model outputs. Incorporating these methods into ML frameworks enables a more robust assessment of prediction reliability [83]. By embedding input uncertainties within the model structure, researchers can significantly improve a model's adaptability and resilience under uncertain environmental conditions.

3.2.2. Parameter Uncertainty

In numerical simulation, parameter uncertainty stems from the selection of model parameters, the establishment of initial conditions, and the specification of boundary conditions. Model parameters are typically derived from watershed characteristics and hydrological data, which can theoretically provide direct or indirect estimates. However, many parameters must still be determined through optimization, making parameter estimation a significant source of uncertainty [84]. The optimization process itself introduces further uncertainties related to calibration data selection, optimization method choice, and objective function design. For instance, the use of inaccurate or unrepresentative calibration data can adversely impact optimization outcomes. Similarly, assumptions and algorithmic choices inherent in different optimization methods can introduce subjectivity into parameter estimates [85]. Objective function design also plays a critical role, as different formulations can lead to varying results, thereby contributing additional uncertainty [86]. Accurately selecting parameters, defining initial and boundary conditions, and optimizing the estimation process thus remain major challenges in numerical simulation. Researchers employed the RF algorithm to correct errors in the large-scale European hydrological model PCR-GLOBWB [34]. By incorporating model state variables, the study achieved significant improvements in streamflow prediction accuracy, reducing model errors across multiple countries.

Floods are complex natural phenomena exhibiting significant geographical and temporal variability, which presents challenges for developing universal models capable of reliably predicting their impacts [87]. Key factors such as flood extent, event duration, terrain morphology, land cover, and rainfall intensity influence the spatiotemporal dynamics of flooding and must be carefully considered in modelling efforts [88]. Consequently, flood models often require regional calibration and customization to accurately reflect local conditions and event-specific characteristics.

A comprehensive understanding of flood dynamics demands the integration of diverse data sources, including hydrological models, topographic data, meteorological records, and satellite imagery. This multi-source data fusion enhances the accuracy of flood simulations and impact assessments [6], thereby supporting informed decision-making throughout the flood management cycle—from preparedness and response to recovery [89].

Remote sensing-based water detection typically relies on spectral band segmentation, where delineation accuracy is highly sensitive to threshold selection. Inappropriate thresholds can lead to substantial errors in identifying water bodies, thereby compromising subsequent analyses [90]. Additionally, the accuracy of water extraction is influenced by the spatial resolution, noise levels, and preprocessing techniques applied to the imagery [91]. To address these challenges, rigorous preprocessing and adaptive thresholding strategies are essential to improve detection reliability.

In machine learning, hyperparameter optimization is critical for addressing model uncertainty, as hyperparameters significantly affect predictive performance. Common optimization methods include manual tuning, grid search, and stochastic search [92]. Manual tuning leverages domain expertise, grid search exhaustively explores predefined parameter spaces, and stochastic search improves computational efficiency by sampling randomly within defined bounds.

Recent studies have applied advanced machine learning techniques in hydrology, with a focus on algorithms such as XGBoost, RF, and stacking ensemble methods. Notably, hybrid architectures combining ANNs with ensemble approaches have been developed to exploit the complementary strengths of different models [93]. These efforts are further supported by novel feature selection techniques, such as Recursive Feature Elimination (RFE), which improve model interpretability and reduce dimensionality [94]. This helps mitigate overfitting, a common issue in high-dimensional hydrological datasets.

Table 3 provides a comparative overview of the four main hyperparameter optimization approaches: manual tuning, network search, random search and multiverse approach. Manual tuning leverages domain expertise and iterative experimentation. Network search exhaustively evaluates predefined hyperparameter combinations. Random search adopts a random sampling strategy within a specified range, potentially achieving superior results with lower computational cost [95]. Multiverse approach is by simulating the expansion and contraction process of the universe, the “white hole” and “black hole” mechanisms are used to efficiently explore the solution space to find the optimal solution, which is particularly suitable for complex multi-peak optimization problems [96]. This table is intended to clarify the advantages and limitations of each approach and guide appropriate method selection for different modelling scenarios.

Table 3. Review of the parameter optimization algorithm.

Method	Advantage	Disadvantage	Reference
Manual tunning	Can be based on previous experience	Highly specialised requirements when selecting a large number of parameters	[97]
Network tunning	Set a range and step size for each parameter when searching	Huge calculation required when have large number of parameters	[98]
Random search	Build the parameters as a stochastic model	Low processing time when have a huge parameter set in deep learning	[99]
Multiverse approach	Strong adaptability; Simple parameter setting; Strong search ability	Lack of theoretical foundation; Randomness	[100]

Optimization algorithms are essential for identifying the optimal hyperparameter combinations. The choice of hyperparameters directly impacts model performance, making it critical to employ optimization techniques to minimize parameter uncertainty effectively. Practical methods such as cross-validation and grid search are commonly used to identify the optimal hyperparameter combinations, enhancing the model’s predictive performance and stability [101]. Overall, parameter uncertainty varies among methods, including indicators and weights for parameter estimation in numerical simulation, segmentation thresholds in remote sensing and telemetry, and hyperparameter selection in machine learning. Each of these aspects involves different degrees of uncertainty. Understanding and managing these uncertainties effectively is crucial for improving the accuracy and reliability of models.

3.2.3. Model Structure Uncertainty

In numerical simulation, model structure uncertainty primarily arises from two key factors. First, the development of model structures often depends on generalizing real-world hydrological processes through mathematical and physical formulations [102]. However, these generalizations are constrained by researchers' understanding of water movement mechanisms. Hydrological modelling is influenced by existing theories and empirical knowledge, which limits the design and flexibility of model structures. For instance, accurately representing nonlinear water flow behaviour or terrain influences is often restricted by current theoretical frameworks and observational experience [103]. As a result, fundamental hydrological processes may be incompletely represented, and the simplifications and assumptions built into models introduce uncertainty, ultimately affecting simulation accuracy.

Flood prediction models often exhibit complex structural configurations [104], requiring the integration of interdependent hydro-meteorological parameters both static and dynamic as model inputs and outputs. These systems demand advanced computational frameworks capable of resolving highly nonlinear dynamics [105]. As a result, the development and optimization of such models remain challenging tasks [106]. Recent advances in machine learning have begun to address these complexities: deep neural architectures and reinforcement learning systems now effectively capture variable interdependencies in hydrological forecasting [107], including flood prediction [108]. Complementing these approaches, ensemble methodologies—which synthesize consensus-based predictions from multiple models—demonstrate enhanced robustness and reliability in hydrological forecasting applications [109].

In this context, researchers have conducted a comprehensive comparative study introducing a novel hybrid architecture specifically designed to address the inherent complexities of hydrological modelling. This architecture integrates state-of-the-art machine learning techniques to enhance predictive performance, key contributions of this study include an innovative combination of XGBoost with traditional methods such as RF and SVR [110]. This hybrid integration not only improves predictive accuracy but also effectively mitigates overfitting an issue commonly encountered in hydrological modelling. Furthermore, the research develops a multi-objective optimization framework that balances prediction accuracy with computational efficiency, thereby offering a rational basis for selecting and deploying machine learning systems [111]. A thorough meta-analysis further demonstrates that hybrid models consistently outperform traditional approaches across a range of hydrological applications [112]. Case studies presented in the research show significant improvements in flood forecasting and groundwater level prediction, highlighting the potential of hybrid models to tackle critical hydrological challenges.

However, the inherent complexity and variability of hydrological systems shaped by both environmental changes and human activities continue to increase model structural uncertainty. Accurately capturing the interactions among factors such as rainfall variability, evaporation, soil infiltration, and anthropogenic impacts remains a significant challenge [113]. Coupled models, which integrate multiple sub-models to simulate complex system behaviours, introduce additional structural uncertainties due to interactions, parameter configurations, and integration methods [114]. In the domain of remote sensing, model structure uncertainty is often linked to the choice of water extraction algorithms decisions that directly influence the accuracy and reliability of the results [115]. Despite recent advancements, significant uncertainties persist. Researchers have reviewed commonly used water extraction algorithms, evaluating their characteristics and applications [116]. Careful algorithm selection is therefore critical to minimizing uncertainties. For example, optical- and radar-based algorithms each offer distinct advantages and limitations [117], depending on the study area, data characteristics, and specific research objectives.

Figure 1 presents a summary of key machine learning algorithms, with a focus on the evolution of ANN architectures. The Single Layer Perceptron (SLP), developed in the 1950s, represents one of the earliest forms of ANNs and consists of a simple architecture without hidden layers. In contrast, the emergence of the Multi-Layer Perceptron (MLP) in the 1970s marked a significant advancement, introducing one or more hidden layers that enabled the modeling of more complex relationships [118]. Deep learning, a more recent and sophisticated subset of ANNs, involves the integration of multiple interconnected neural networks to process and learn from complex data [119]. Notably, its defining feature lies not merely in the number of hidden layers but in the depth and architecture of the network as a whole. This figure illustrates the progression from basic to advanced ANN models—SLPs, MLPs, and deep learning—highlighting improvements in predictive accuracy and computational capability with each stage of development.

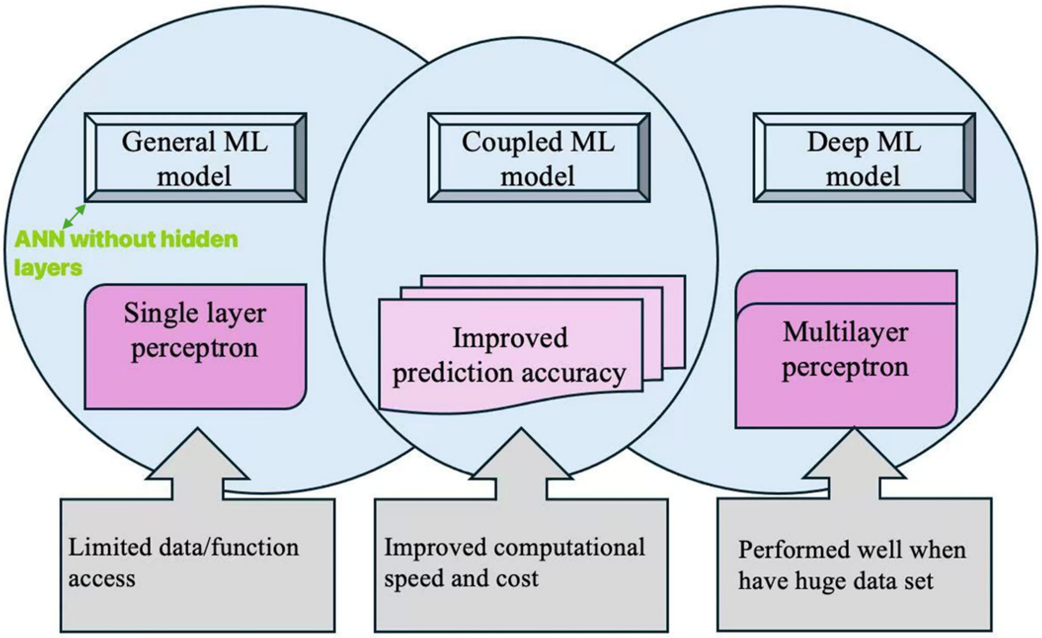

Figure 1. Comparison and summary of Machine learning algorithms.

4. Machine Learning in Flood Risk Assessment

In recent years, ML methods have become valuable tools for flood risk assessment. These techniques leverage intelligent algorithms to automatically identify flood risk characteristics and the relationships between driving factors, enabling flexible, objective, and rapid evaluations. A range of ML models have been applied to flood risk assessment with promising results [120]. Researchers found that the random forest model outperformed SVM in flood risk prediction tasks [121].

The growing demand for reliable flood risk assessment maps has driven further innovation. Researchers have trained flood-related datasets using backpropagation (BP) neural networks, generating risk distribution maps that closely aligned with results from the energy-value method [122]. Similarly, a survey showed that the XGBoost model could produce high-quality, county-level flood risk maps [123]. Researchers integrated deep learning networks with hierarchical analysis to create regional flood risk assessment maps, demonstrating improved accuracy through method integration [124]. A study developed an indicator system that incorporates causative factors, exposure, and vulnerability for predicting heavy rainfall and flood disasters. They constructed BP and XGBoost models and found that the combination of these indicators achieved superior prediction accuracy, even without the use of principal component analysis for dimensionality reduction [125].

More recently, coupled machine learning methods have emerged as advanced strategies for enhancing model performance. By integrating optimization techniques that address both local and global objectives, these methods improve predictive accuracy, computational efficiency, and operational cost-effectiveness particularly in scenarios involving under-trained datasets.

Table 4 presents examples where incorporating additional parameters into coupled models significantly enhanced prediction outcomes. It also highlights specific optimization strategies and their practical applications in managing complex data environments.

Table 4 outlines the optimization strategies utilized in coupled machine learning models for flood prediction. Researchers introduced a combined model integrating CNN, XGBoost, and PLS regression to enhance inflow prediction accuracy. The data were divided into low-flow and high-flow subsets, with a specialized inflow-weighted loss function designed to prioritize accurate prediction during high-flow events. A two-layer stacked ensemble was constructed, where CNN, XGBoost, and PLS served as base learners. In the second layer, linear regression was employed to mitigate overfitting [123]. The ensemble model significantly reduced RMSE compared to individual models. Five-fold cross-validation was applied, and the predictions from base learners were used to train the meta-learner, further optimizing model performance. A hybrid deep learning model, ConvLSTM, was developed to combine the spatial feature extraction capabilities of Convolutional Neural Networks (CNN) with the temporal sequence modeling strengths of Long Short-Term Memory (LSTM) networks [126]. The

ConvLSTM architecture consists of three layers: a ConvLSTM2D layer with 128 filters and ReLU activation, a flattening layer, and a dense output layer. Using a batch size of 100 and the Adam optimizer, the model was trained on precipitation data represented by the Flood Index (IF), which evaluates flood duration, severity, and intensity. By integrating historical and real-time rainfall data, the ConvLSTM model predicted daily IF values, achieving RMSE values below 0.3 across four station prediction cycles, with Legate-McCabe Efficiency (LME) indices ranging from 0.726 to 0.939 [126]. These findings highlight ConvLSTM's potential utility for disaster management and risk mitigation during extreme weather events.

Table 4. Specific optimization method of coupled machine learning methods.

Direction for Improvement	Model	Improvement Method	References
Input data	ConvLSTM	ConvLSTM is a hybrid variant of the LSTM architecture that uses convolution operators rather than matrix multiplication for state inputs and state-to-state transitions. This allows the algorithm to process spatio-temporal data and use inputs from local neighbours and previous states to determine the upcoming state of a particular cell in the grid	[126]
Function	ANFIS optimised using genetic algorithms	A hybrid machine learning model using Adaptive Neuro-Fuzzy Inference System (ANFIS) and Genetic Algorithm which is trained based on temperature, precipitation data and river level from two weather stations. Different AFIS models with different affiliation functions and optimisation techniques were tested and the best performing model was selected for further modification. The parameters of the selected ANFIS model are then optimised using genetic algorithms to obtain better results	[127]
Function	BiLSTM	Adding a VMD decomposes and preprocesses the data to remove noise and uses the SSA algorithm to intelligently find the two parameters of the VMD. Constructed a two-layer BiLSTM neural network and used the Relu activation function instead of the traditional sigmoid activation function to reduce gradient descent and gradient vanishing during the prediction process	[128]
Data pre-processing	CNN & XGBoost & PLS Use double layer stacking	Noise reduction using data preprocessing, streaming the dataset, introducing a special loss function, and combining the three model overlays to improve prediction accuracy	[123]

To enhance nonlinear inference capabilities, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has been employed. Based on the Takagi-Sugeno Fuzzy Inference System framework, ANFIS enhances learning by adjusting system structures and parameters using neural learning algorithms [127]. Researchers further advanced this approach by integrating ANFIS with a genetic algorithm to optimize membership functions and overcome the training limitations of conventional feedforward neural networks in forecasting the water levels of the Jhelum River.

Although LSTM-based models have improved water level prediction accuracy, their unidirectional information flow restricts the ability to capture both past and future temporal dependencies. To overcome this limitation, researchers proposed bidirectional learning architectures such as BiLSTM. In particular, one study developed a BiLSTM attention network for flood risk prediction, in which Variational Mode Decomposition (VMD) was used to decompose the input signals into Intrinsic Mode Functions (IMFs) [128]. Each IMF was then fed into a two-layer BiLSTM-attention network. Particle Swarm Optimization (PSO) was employed to fine-tune both VMD and BiLSTM parameters, significantly reducing storage errors and enhancing predictive accuracy—especially for peak height and arrival time estimations [129].

Traditional statistical methods such as ARMA, ARIMA, and Multiple Linear Regression (MLR) have been widely used in flood frequency prediction, with ARIMA generally outperforming ARMA [130]. In contrast, machine learning models—such as artificial neural networks, neuro-fuzzy systems, support vector machines, and support vector regression—have demonstrated higher predictive efficiency in many applications [131]. Hybrid modeling approaches further improve performance; for instance, fuzzy reasoning systems grounded in fuzzy logic have shown strong capabilities in modeling nonlinear hydrological phenomena [132].

Building on this, researchers introduced a BiLSTM attention model tailored for flood prediction tasks [133], integrating Particle Swarm Optimization to fine-tune parameters and enhance forecasting robustness [134].

The final model, which combines multiple strategies, demonstrated superior generalization and lower RMSE compared to standard LSTM, BiLSTM, and CNN-BiLSTM configurations. It proved especially effective in high-risk flood forecasting scenarios [79]

The development of hybrid and coupled machine learning models marks a major advancement in flood prediction and risk assessment. Models such as ConvLSTM effectively leverage both spatial and temporal data to surpass the limitations of traditional approaches, while attention-based BiLSTM architectures capture complex bidirectional dependencies, enhancing robustness [135]. However, these models require careful optimization and validation to avoid issues like overfitting and to maintain generalizability across varied flood scenarios. The integration of optimization techniques like Particle Swarm Optimization introduces adaptive capabilities but also adds computational complexity [136]. Meanwhile, ensemble approaches like the CNN-XGBoost-PLS model highlight the value of combining different algorithms to enhance predictive power and reduce model bias [137]. Nevertheless, these hybrid frameworks depend heavily on data quality, segmentation strategies, and validation frameworks, emphasizing the ongoing need for rigorous testing to ensure practical applicability in diverse environmental contexts.

5. Summary of Machine Learning Models in Flood Risk Assessment

To ensure the comprehensiveness and reproducibility of this review, a structured literature search was conducted using the Scopus database. The search employed the keywords “flood hazard assessment method” and “machine learning,” applied to article titles, abstracts, and keywords. The search was limited to publications from 2019 to 2024 to capture recent advancements in the field. This initial query yielded approximately 188 records.

After removing duplicates, the remaining articles underwent a multi-stage screening process, beginning with title and abstract reviews, followed by full-text evaluations based on predefined inclusion and exclusion criteria. Studies were included if they met the following criteria: (1) written in English; (2) published in peer-reviewed journals; and (3) focused explicitly on the application of machine learning techniques to flood-related tasks, including real-time forecasting, flood risk mapping, simulation modeling, early warning system optimization, and post-event impact assessment.

To maintain methodological rigor and technical relevance, several exclusion criteria were applied. Specifically, the following types of publications were excluded:

(1) Editorials, letters, opinion pieces, and review articles that lacked original modeling contributions;
(2) Studies that did not utilize machine learning algorithms, such as those relying exclusively on conventional hydrological models (e.g., HEC-RAS, SWAT) or remote sensing–based monitoring;
(3) Grey literature, including preprints, technical reports, and government publications;
(4) Non–peer-reviewed materials; and
(5) Studies where machine learning was used only as a supplementary tool—for example, for image preprocessing or data imputation—rather than as the core of the modeling framework.

Following this rigorous screening process, a total of 174 high-quality studies that met all inclusion criteria were selected for in-depth analysis. These studies form the analytical foundation for the discussions and comparisons presented in the subsequent sections.

A slight decline in the number of publications was observed in 2024, possibly reflecting a shift in research focus toward the integration of emerging technologies such as artificial intelligence and big data analytics in flood hazard assessment.

Although this review centers on literature from 2019 to 2024, it is important to acknowledge several seminal studies from earlier periods that laid the groundwork for current methodologies. For instance, early work introduced GA-ANN hybrids for real-time flood prediction [138], demonstrated the efficacy of wavelet-based preprocessing in enhancing ANN model performance [139], and explored the use of ANFIS-based flood models as early as 2011 [140]. A comprehensive review of machine learning applications in flood modeling up to 2018 was also conducted [141]. These foundational contributions paved the way for the more advanced and hybridized techniques examined in recent years.

The intensification of global climate change has led to a notable increase in the frequency and severity of extreme weather events, contributing to a rise in natural disasters such as flooding [142]. This trend has driven growing academic interest in flood risk assessment methods, resulting in a surge of related publications [143]. In parallel, technological advancements—particularly in remote sensing, data analytics, and modeling—have introduced new tools and methodologies, further stimulating research in this area [144].

The slight downturn in publications in 2024 may suggest research saturation in traditional approaches or a redirection toward novel methods. Future research should focus on integrating existing assessment techniques with cutting-edge technologies to better address the complexities of environmental change and evolving policy demands [145].

ML in hydrology faces several persistent challenges. Data availability and quality are often limited by incomplete or biased historical datasets, which undermine model robustness and generalizability. The "black box" nature of advanced ML architectures particularly hybrid and stacked models reduces transparency and erodes stakeholder trust. Moreover, although model interpretability is widely recognized as a critical need, detailed methodologies to enhance it are rarely reported, leaving a gap between awareness and practical implementation [146]. The high computational demands of training complex ML models further constrain their scalability, particularly for real-time applications, where balancing model complexity and computational efficiency becomes essential. Additionally, many ML approaches implicitly assume stationarity, limiting their adaptability to evolving environmental conditions such as climate variability [147]. The heterogeneity and noise inherent in hydrological datasets can degrade model performance and stability, particularly when models are applied across diverse settings. Overfitting remains a significant concern, especially when working with small or narrowly defined datasets, further diminishing generalizability. Finally, the absence of standardized evaluation metrics hampers model benchmarking and the identification of optimal approaches for specific hydrological applications.

Figure 2 presents a systematic literature summary of machine learning models in flood risk assessment. Based on the literature statistics, ANN and RF are the most widely used machine learning models, corresponding to the highest number of articles, respectively. This phenomenon reflects these two models' strong fitting ability and predictive accuracy in flood risk assessment. ANN is favoured for its flexibility and nonlinear modelling ability, while RF is widely used for its excellent noise immunity and advantages in handling high-dimensional data. Researchers chose these well-established models to solve complex flood risk assessment problems. LSTM is a deep learning model for processing time series data, has a relatively small number of applications but still shows significant potential. The ability of the LSTM model to capture long-term dependencies in time series data makes it a promising application for flood prediction. Models such as SVM, Radial Basis Function (RBF), and XGBoost appear less frequently in the literature and have also begun to appear in application articles since 2022, which may reflect either the limitations of these methods in specific application scenarios or the researchers' preference for more advanced model selection. In addition, the emergence of Hybrid ML models shows researchers' interest in integrated approaches that combine the strengths of different models to improve prediction performance. However, their literature volume has not yet reached the level of mainstream models, indicating that there is still room for further exploration in this area.

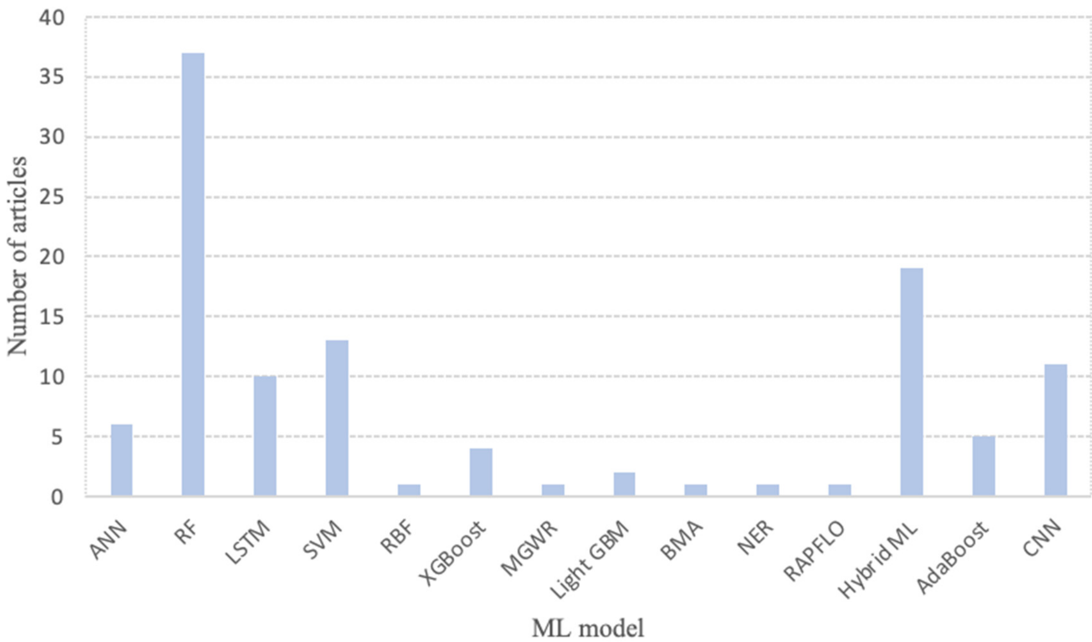

Figure 2. Summary of machine learning model applied in flood risk assessment.

6. Future Perspectives

Flood hazard assessment, particularly in flood forecasting, often faces significant challenges when relying solely on a single machine learning model. The practical application of such models is limited by uncertainties in input data, model structure, and parameter selection, all of which can undermine forecasting effectiveness. To overcome these limitations, researchers have increasingly adopted hybrid models, which integrate machine learning with other approaches or optimization techniques to leverage the strengths of multiple models and enhance predictive performance.

Hybrid models improve flood forecasting accuracy through systematic optimization of inputs, structure, and parameters. To refine input data, techniques such as grey relational analysis, mutual information, and cross-correlation are employed to identify the most relevant variables. Grey relational analysis evaluates relationships between variables, while mutual information and correlation methods quantify informational value, filtering out less significant features. These techniques reduce input uncertainties and establish a more reliable foundation for prediction.

Optimizing model structure is another key aspect of hybrid modelling. Techniques such as genetic algorithms are used for feature extraction, simulating natural selection processes to optimize feature subsets. Meanwhile, context-aware mechanisms and spatiotemporal attention techniques adjust model weights dynamically, enabling the model to better capture evolving patterns over time. By integrating these approaches, hybrid models become more adaptable and capable of addressing the complexity inherent in hydrological data.

Parameter optimization further enhances hybrid model performance. Methods such as genetic algorithms, particle swarm optimization, and ant colony optimization efficiently explore parameter spaces to identify optimal configurations. The bootstrap method is also widely employed to assess model uncertainty, evaluating stability and generalizability through resampling techniques. These advanced optimization strategies significantly contribute to improved prediction accuracy and model robustness.

Hybrid models offer a promising pathway for advancing flood forecasting by combining different modelling strategies. They can integrate machine learning models with physical process models and hydrodynamic models to simulate rainfall-runoff processes more accurately. Physical models provide detailed representations of hydrological processes, while machine learning models excel at capturing complex, nonlinear relationships. Alternatively, hybrid models can combine multiple machine learning models through ensemble learning methods, which aggregate diverse predictions to improve accuracy, generalization, and computational efficiency.

This article classifies popular machine learning models in flood forecasting into traditional and deep learning models based on structural complexity. Traditional models often struggle to capture historical temporal information and demonstrate limited learning capabilities. In contrast, deep learning models excel at extracting temporal patterns, but face challenges related to complex architectures and high computational demands. Hybrid models address these challenges by optimizing inputs, structures, and parameters, thereby improving prediction accuracy, extending the forecast horizon, and meeting practical needs from a multidimensional perspective.

Hybrid modelling is becoming a significant trend in flood forecasting research. Future efforts should focus on deeper integration of physical process-based models with machine learning techniques to achieve more accurate simulations of water flow and flood risks. Enhanced flood forecasting can support more effective flood mitigation strategies and reduce societal and environmental impacts. By combining the strengths of various modelling approaches and continuously optimizing inputs, structures, and parameters, hybrid models have the potential to substantially improve the accuracy and reliability of flood forecasts. Researchers should continue to explore optimization strategies and incorporate the latest technological advances to further enhance flood early warning systems and provide more effective solutions to the growing challenges posed by climate change and increasing flood risks.

7. Conclusions

This paper reviews significant machine learning models used in flood hazard assessment, categorizing them into traditional and deep learning models, further divided into short-term and long-term predictions. It highlights research from 2019 to 2024, analyses representative models, and discusses their advantages, limitations, and future development. In flood forecasting, model selection is influenced by accuracy, speed, data requirements, and practical application concerns.

Traditional hydrological models simulate detailed watershed processes and provide valuable insights. They require extensive data and are computationally intensive, which limits their flexibility. In contrast, data-driven machine learning models are more accessible to construct and implement, but they demand high-quality data and often lack interpretability. Traditional machine learning methods, such as decision trees and random forests, struggle with temporal data. Deep learning models excel in processing temporal information but come with higher computational costs due to their complexity. Machine learning has the potential to significantly enhance the accuracy and reliability of flood forecasting by analysing vast datasets to uncover complex relationships and patterns, thereby offering a more comprehensive understanding of flood risks. However, the application of machine learning in flood prediction requires careful consideration of its limitations and potential pitfalls. Ensuring data quality, regularly updating models, minimizing bias, and preventing overfitting are critical to maintaining model reliability and performance. Despite these challenges, ongoing advancements in machine learning are expected to drive more sophisticated and effective forecasting solutions. Staying abreast of emerging developments and continuously exploring new applications of machine learning remains essential for maximizing its potential across diverse domains.

To address these limitations, hybrid models have emerged, combining the strengths of various approaches to enhance forecast accuracy and generalization. By integrating the advantages of different models, hybrid approaches improve forecasting periods and meet practical requirements. With advancements in machine learning and the increasing informatization of water conservancy, the demand for sophisticated models is rising. Future applications of machine learning are expected to significantly impact flood forecasting, watershed management, and water resource optimization, providing innovative tools for intelligent water management.

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Conflicts of Interest

The authors declare no conflict of interest.

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