Machine Learning-based Hydrological Models for Flash Floods: A Systematic Literature Review

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Abstract

Background & Purpose: Flash flood modeling faces many challenges since physically-based hydrological models are unsuitable for a small spatiotemporal scale. With the increased availability of hydrological observed data, an alternative approach is to use machine learning (ML) techniques. This work conducts a Systematic Literature Review (SLR) to enhance our comprehension of the research landscape on ML applications for modeling flash floods. **Methods:** Starting with more than 1,200 papers published until January 2024 and indexed in Web of Science, SCOPUS/Elsevier, Springer/Nature, or Wiley databases, it was selected 50 for detailed analysis, following the PRISMA guidelines. The inclusion/exclusion criteria removed reviews, retractions, and papers that were not in the scope of this SLR and included only papers that used data with a temporal resolution finer than 6 hours. From each selected paper, among other information, data were extracted regarding the forecasting horizon, the size of the study area, the different input data, the chosen machine learning (ML) technique, and the type of outcome (whether regression or classification) in order to characterize the model applied to flash flood forecasting. **Results and Discussion:** There has been a notable increase in publications investigating ML techniques for flash flood modeling over the last few years. Most of the studies are performed in China (38%). In 49 out of 50 of the selected papers used as input data, just one or an exclusive combination of the following measurements: discharge, rainfall, and water level. From this set, the combination of discharge and rainfall appears in almost 40% of the papers. Notably, 60% of the studies utilize the long short-term memory (LSTM) method. No method consistently outperforms all others in the selected papers. Unfortunately, only 10% of the selected articles provide access to their data. To further explore the potential of ML approaches in flood forecasting, we recommend their integration into early warning systems, development and dissemination of benchmarks, publication of successful case studies, and multidisciplinary collaboration.

Keywords: artificial intelligence, machine learning, flash floods, hydrological modeling, disasters

GLOSSARY

Term	*Description*	*Term*	*Description*
AE	Autoencoders	GAN	Generative Adversarial Network
ANFIS	Artificial Neural Network and Fuzzy Inference System	GRU	Gated recurrent units
ARMA	Autoregressive–Moving-Average	k-NN	K-nearest neighbors algorithm
BMA	Bayesian Model Averaging	LSTM	Long Short-Term Memory
CGBR	Categorical Gradient Bosting Regression	MARS	Multivariate adaptive regression spline
CNN	Convolutional Neural Networks	MLP	Multilayer Perceptron
Conv-LSTM	Convolutional Long Short-Term Memory	OPENML	Open Machine Learning
DANN	Domain-Adversarial Neural Network	PSO	Particle swarm optimization
DNN	Deep Neural Network	RF	Random Forest
DSTGNN	Dynamic Spatiotemporal Graph Neural Network	RNN	Recurrent neural network
DT	Decision Tree	SVM	Support Vector Machine
ED	EnconderDecoder	XGBoost	Extreme Gradient Boosting
ELGBDT	Extreme Learning Machines and Gradient Boosted Decision Trees		

1 Introduction

Nearly 44% of disasters worldwide have been associated with floods, and different types of floods account for 31% of economic losses [1]. It is estimated that from 2000 to 2024, floods affected over 1.8 billion people and caused a global annual average economic loss of US$ 38.88 billion [2]. Compounding this issue, ongoing global climate change is anticipated to raise the frequency and severity of such events [3, 4].

Flash floods are among the most common types of natural disasters worldwide [5, 6]. They are often defined based on observations of river streamflow or water levels, with several quantitative metrics emphasizing the significance of a high peak discharge or a rapid rise in water level (typically within <6 h) [7], usually triggered by heavy rainfall [8], quick snowmelt [9], or induced by dam and levee breaks [10]. One example of a flash flood metric, for instance, is the Flashiness-Intensity-Duration-Frequency (F-IDF) curve, which is based on the frequency and duration of various rainfall events [11]. Although there is no general consensus among the scientific community regarding a metric that defines flash floods, their triggering rainfall events typically occur on a small spatiotemporal scale. Regardless of the climatic study area, they are predominantly observed in urban locations with steep terrain or inadequate drainage systems, particularly in regions prone to severe weather events [4, 6]. Smaller and steeper watersheds respond more rapidly to intense precipitation, resulting in a shorter time lag between the onset of heavy rainfall and the rise of water levels or river discharge. This can provide less warning time to residents and emergency responders [8].

Hydrological models are employed to study the hydrologic cycle, representing a component (or stage) of it [12]. There are many forms of hydrological models since they are designed to deal with different problems. These models take into account multiple factors, such as catchment characteristics and the spatial and temporal variations in rainfall [13], which can effectively characterize flash flood behaviors. Consequently, they serve as crucial tools for flash flood prediction and for issuing timely warnings.

Despite advances in physically-based hydrological models [14], such models are typically applied to flood forecasting in larger watersheds with slower responses. They are not designed to detect rainfall and runoff variations that occur on a small spatiotemporal scale, which can lead to flash floods. To monitor trigger mechanisms, operational flash flood forecasting relies on high-resolution remote sensing data, such as weather radar, to estimate accumulated rainfall volumes or utilize weather numerical models to forecast precipitation at short lead times [6]. The increased availability of observed hydrological data (e.g., water levels and discharge) has led to an increase in the usage of data-driven hydrological models, in which time series of river levels or discharges are predicted without needing to know the physical parameters related to the watershed [15]. Given the availability of good-quality observed data, data-driven models can more accurately predict river dynamics responses, requiring less computational time and calibration than physically-based hydrological models [16].

Artificial intelligence (AI) is a broad field of research dedicated to creating systems that use computer programs to mimic human intelligence and cognitive processes. These systems aim to perform tasks such as reasoning, learning, adaptively interacting with their environment, and making decisions without explicit instructions [17].

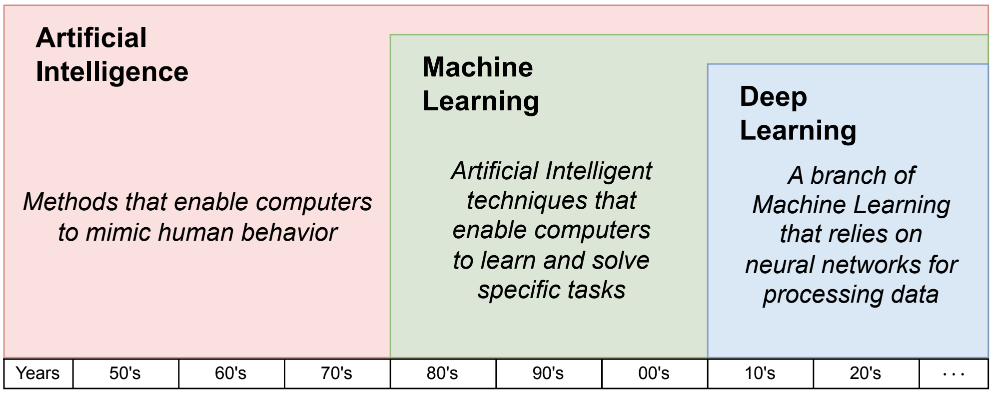

Figure 1 Artificial intelligence (AI) trend towards deep learning (DL) for hydrological forecast/prediction over the years.

Among the various approaches to designing AI systems, the most notable is the application of machine learning (ML) techniques, which generally rely on the principle of learning exclusively from data [18]. It is important to highlight that the significant progress AI has made in recent years can be largely attributed to improvements in the predictive capabilities of ML techniques, particularly through deep learning (DL) (see Figure 1).

As a result of the remarkable growth of ML methodologies in hydrological modeling, there is a need for periodic literature reviews aimed at identifying significant advancements and challenges within this area. In 2014, a considerable contribution to this field was presented by [19], where the authors conducted a comprehensive examination of contemporary advancements and the potential utility of support vector machine (SVM) techniques within hydrology. In the following year, [20] investigated the use of ML for streamflow forecasting from 2000 to 2015. The research revealed that over the examined years, ML methods showed substantial advancements in hydrological forecasting and simulation, effectively capturing complex information in the data that previous methods could not.

Since 2021, there has been a significant increase in the publication of review articles focused on applying ML in the field of hydrology. Notably, we highlight the work by [21], in which the authors explored the progress of employing ensemble methods across various hydrological application domains. Their findings indicate a general trend of superior performance compared to traditional ML models. In the context of runoff, a thorough examination is presented in [22], where the authors evaluated the specific use of adaptive neuro-fuzzy inference systems (ANFIS), artificial neural networks (ANN), and SVM for runoff simulations. The primary goal of this review was to clarify the main advantages and limitations of each of these methodologies. Additional reviews on the use of ML in hydrological contexts can be found in [23–25].

Furthermore, With the advancement of scientific repository search tools, the potential for methodically organizing and reproducing literature review protocols has emerged, leading to the establishment of a paradigm known as *Systematic Reviews* [26]. In [27], a systematic review is conducted on the state-of-the-art ML and DL methods in predicting hydrological processes, climate changes, and earth systems. Other more general systematic reviews involving hydrology can be found in [28]. Given this context, this paper conducts a Systematic Literature Review (SLR) to enhance our understanding of machine learning applications for modeling flash floods. To the best of our knowledge, this represents the first comprehensive literature review on ML models for flash floods. We outlined the scope of the review to address key questions regarding flash flood forecasting while maintaining conciseness.

2 Methodology

This review covers articles on ML and hydrological models through an extensive search in large scientific databases; for this purpose, it follows the process suggested by [29, 30], and the resources of *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* - also known as PRISMA 2020 - to make the review transparent and replicable. A table with all processed steps and the PRISMA 2020 checklist is available at https://github.com/rogerionegri/iFAST.

Our search strategy employed keywords relevant to the research questions, utilizing Boolean operators (AI, ML, DL, hydrology, hydrological model, hydrological forecast, flood, rainfall-runoff, fast response, fast dynamic, rapid response, rapid dynamic, short lead time, and/or short-term forecast). These terms were organized into overarching concepts or tiers. We used "OR" to encompass synonyms and alternative spellings while using "AND" to connect primary terms with secondary ones. Articles published in peer-reviewed journals in the English language were considered up until December 2023. The following databases were consulted: Web of Science, SCOPUS/Elsevier, Springer/Nature, and Wiley. The searches included paper titles, keywords, and abstracts. No limit was imposed on the number of articles returned in the query. Additionally, we included 20 other papers based on our prior knowledge of the literature.

In the first screening process, we eliminated duplicated papers. In the following screening, we excluded reviews, retractions, and papers that fell outside the review's scope, primarily focusing on topics such as rainfall forecasting, groundwater forecasting, flood mapping, coastal flooding, and tsunami forecasting, as well as papers containing data with a time resolution coarser than 6 hours. Consequently, the final set of papers for this review consists of 50 papers. From this final set of ML models for flash floods, we analyzed various characteristics. A datasheet containing all 50 selected papers and their attributes can be found at https://github.com/rogerionegri/iFAST. A summary of the attributes considered in this study is presented in Table 1. Lastly, the PRISMA diagram for this systematic review is presented in Figure 2.

3 Results and Discussion

Figure 3 shows the number of publications, both yearly and cumulatively, related to the topic of this review. It is clear that there has been a significant increase in recent years, especially after 2021, with a large number of papers published in 2023. This

Table 1 Summary of attributes observed in the reviewed papers.

Attribute	Description
area of study	country in which the research is carried out
data availability	if data is public
input data	input data used in the model(rainfall, water level, or discharge)
lead time (min)[h]	minimum forecast horizon
lead time (max)[h]	maximum forecast horizon
ML main method	type of ML method
model output data	level, discharge, or both
regression, classification, or both	the model predicts categories or classes for each element, respectively
remote sensing	if the paper uses remote sensing data (radar or satellite)
temporal resolution (min)	temporal resolution of input data

growth may be attributed to either the increasing frequency of flash floods caused by recent climate changes or the newly available proposed ML methods.

The top seven journals encompass a diverse range of fields, from hydrology to applications of computer science. Regarding the frequency of articles reviewed per journal, as shown in Figure 4, *Water* (MDPI) and *Journal of Hydrology* (Elsevier) are the two main sources of research on ML for modeling flash floods.

3.1 In which countries is research on machine learning (ML) and flash floods most commonly found?

Figure 5 illustrates a spatial representation of the number of studies conducted across various regions of the globe. This representation highlights that the revised studies encompass 20 countries spread throughout Asia, Europe, and North and South America. The majority of the study areas are situated in Asia, particularly in China (38%) and the Republic of Korea (8%), as well as in the United States (8%).

This scenario may reflect the fact that China and the United States are among the countries with the most experience in dealing with floods in the world, alongside India, Indonesia, the Philippines, and Brazil [31]. China is the country most severely threatened by flood disasters worldwide, with damages from these events between 1990 and 2017 accounting for about 10% of the total damage in the world. [32]. Flash floods, in particular, are widely recognized as a significant cause of human casualties and economic losses in China [33, 34]. From the American perspective, flash floods result in the highest number of casualties among various flood events in the U.S. [35, 36]. American national assessments have shown that the eastern U.S. frequently experiences flood events, accounting for a substantial proportion of the country's flood-induced fatalities. This is partly due to tropical cyclone-related precipitation, which contributes nearly 30% to annual rainfall in the region due to its geographic position [37]. Finally, looking at the Republic of Korea, most small urban river basins in the country have a very short concentration time, which leads to frequent and deadly accidents caused by flash floods during located heavy rainfall [38].

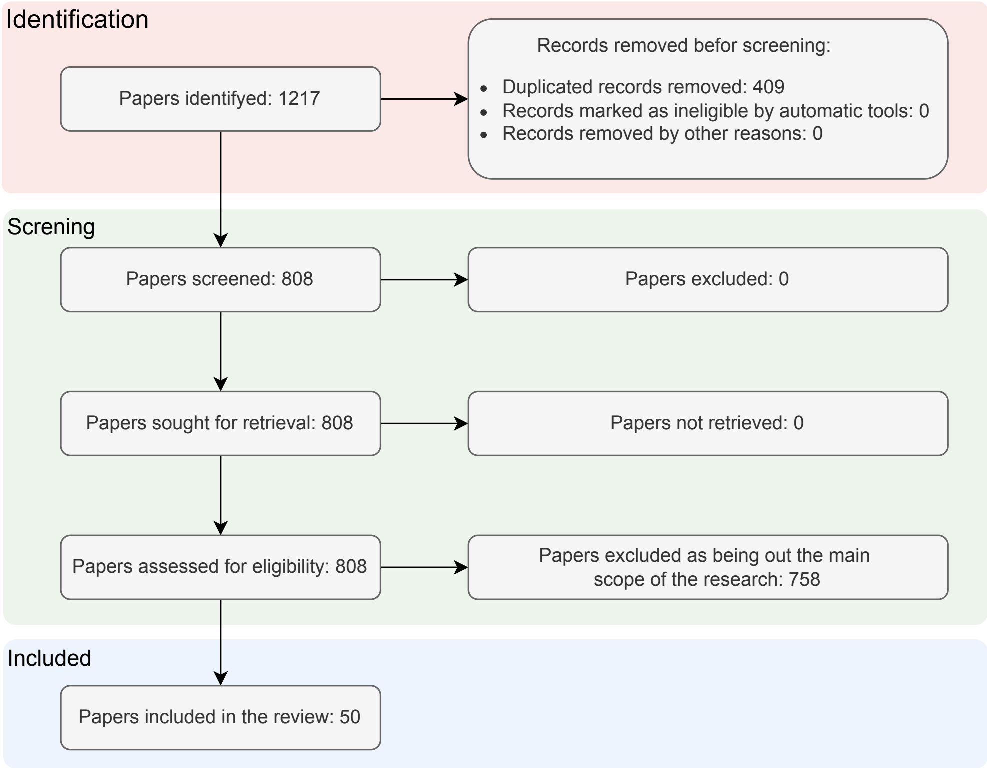

Figure 2 The PRISMA 2020 workflow diagram.

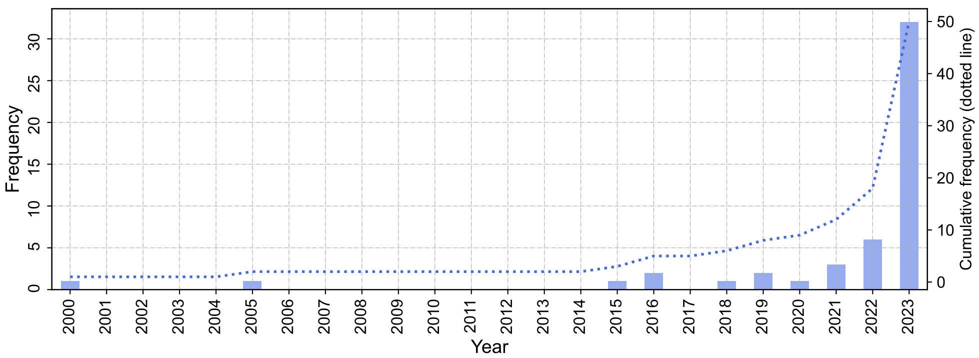

Figure 3 Absolute and cumulative number of publications about machine learning (ML) applied to flash floods per year.

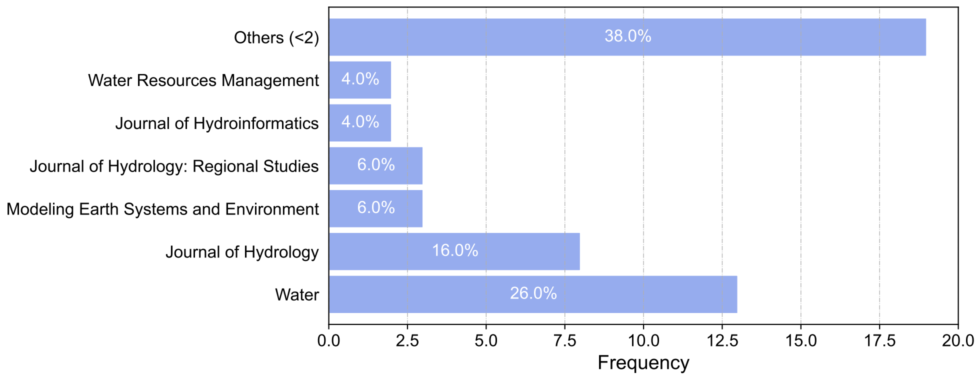

Figure 4 Frequency of articles using machine learning (ML) for flash flood hydrological modeling by journal.

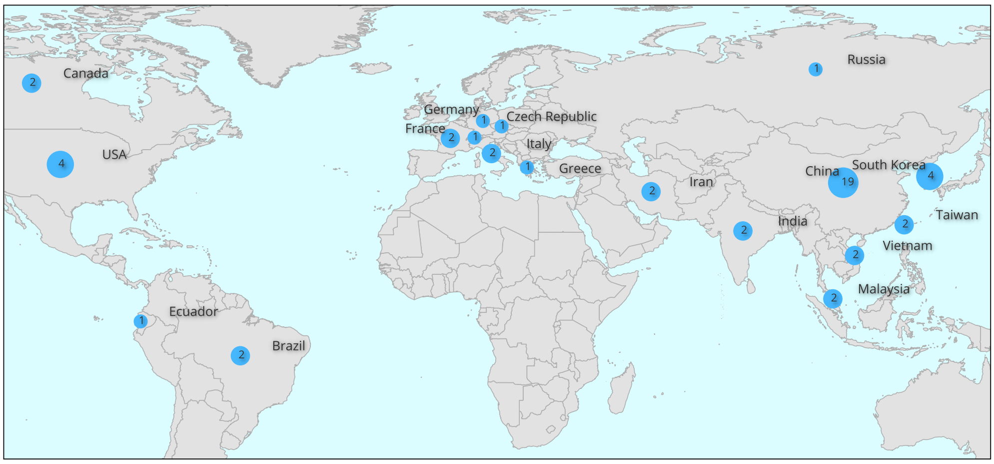

Figure 5 Frequency of articles applying machine learning (ML) to flash floods according to country application.

3.2 What are the most commonly used input and output data in machine learning (ML) models for flash floods?

Among the 50 selected articles, rainfall is the most commonly applied input variable, appearing in 44 studies (88%). Discharge data is included in 23 studies (46%), and water level data is employed in 19 studies (38%). 49 articles employed only one or a specific combination of the following measurements: discharge, rainfall, and water level. Only one study used runoff as the sole input data [39]. Notably, four papers (8%) combined rainfall, water level, and discharge data simultaneously. Additionally, four studies relied solely on rainfall data, three studies (6%) on water level data, and two studies (4%) on discharge data. Figure 6 illustrates the distribution of the input data used in the 50 studies analyzed in this work.

It is important to note that discharge and rainfall are the most common combinations in these studies and are also suitable for physically based models. Studies that utilize water level data in ML applications for flash flood prediction hold significant potential, as obtaining water level data is often easier than acquiring discharge data [40].

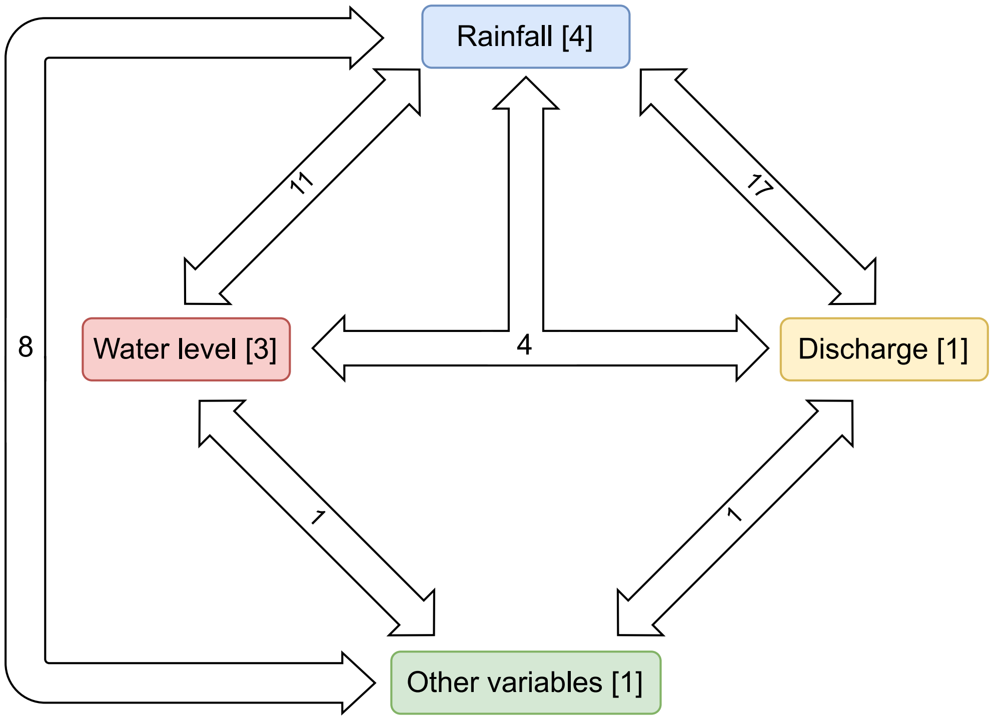

Figure 6 Distribution of the input data applied by the 50 analyzed articles. Values between [] mean the number of papers where the input data was employed solely; values within the arrows mean the number of papers that share the input data.

Among the selected articles, 30 papers (60%) reported discharge as output, while 19 works(38%) indicated water level as output. Remarkably, only one article (2%) did not present either the discharge or water level as output. In [41], dynamic clustering and random forest techniques were employed to identify flood types and select suitable model parameters. Following this, the Xinanjiang model for real-time flood forecasting was implemented. In this method, three flood indicators were recognized as the most crucial factors characterizing flooding: flood duration, peak discharge, and runoff depth.

Lastly, while more than half of the articles provided discharge and water level as the outputs of their studies instead of a flood extent map, most utilized historical flooding event records in their simulations, for instance, to train a neural network or to endorse and validate their findings, as referenced in [42–47].

3.3 What are the most common machine learning (ML) techniques for modeling flash floods?

Table 2 presents a list of the most commonly used ML methods for modeling flash floods. It also provides a brief description of each method and the respective papers that feature them as one of the main methods (those demonstrating the best performance). Furthermore, the frequency of each ML method applied to hydrological modeling is illustrated in Figure 7. LSTM is the most utilized method, appearing in 60% of the works, followed by MLP, which is used in 28%. The revised studies also employed CNN, tree-based methods (decision trees or random forests), and SVM, used in 16%, 16%, and 14% of the papers, respectively. Other methods, such as k-Means, KNN, Extreme ML, Particle Swarm Optimization, and Fuzzy-based methods, were employed less frequently.

Figure 8 shows a comparison of all ML methods presented in the articles, including both result comparison methods and the main methods, which represent the highest performance in each paper. Notably, LSTM was utilized and ranked as one of the best methods in this set of papers. However, no single method consistently outperforms all others. Therefore, it is essential to explore various methods for each research problem to determine the most suitable approach for each case study.

Table 2: List of the most used ML methods for modeling flash floods.

Method	**Short Description**	**Papers in this review**
AE [48]	Neural network architecture designed for unsupervised learning that learns to encode input data into a latent representation and reconstruct it with minimal loss.	[49]
ANFIS [50]	Hybrid system that combines fuzzy logic and NN techniques for adaptive modeling and inference.	[51]
ARMA [52]	Combines autoregressive and moving average components to predict a time series based on its own past values and error terms, balancing short and long-term dependencies	[53]
BMA [54]	Statistical technique that combines Bayesian models in a temporal framework, considering changes in relationships between variables over time.	[55]
CGBR [56]	Advanced ensemble model that incorporates ordered boosting for categorical features. It employs minimal variance sampling to balance tree growth, enhancing prediction accuracy and computational efficiency.	[57, 58]
CNN [59]	Deep learning architectures adept at processing structured grid data, utilizing convolutional layers to learn hierarchical features automatically.	[47, 60–63]
Conv-LSTM [64]	Integrates convolutional operations within LSTM units. It processes input sequences by convolving spatial features and capturing temporal dependencies simultaneously, enhancing the model's ability to learn spatiotemporal patterns efficiently.	[47, 57, 61]
DANN [65]	The Dynamic that adjusts the structure of the neural network during training	[66]

Method	Short Description	Papers in this review
DNN [67]	Deep Neural Networks learn complex features by passing data through multiple layers of interconnected nodes, or neurons, mimicking human brain function for tasks like image recognition and natural language processing	[46]
DSTGNN [68]	Method for modeling dynamic spatiotemporal data, leveraging GNN to capture spatial dependencies and temporal dynamics efficiently	[69]
DT [70]	A machine learning algorithm that recursively partitions data based on feature values to create a predictive model represented by a tree-like structure	[71–74]
ELGBDT [75]	An ensemble learning technique that combines the strengths of Extreme Learning Machines and Gradient Boosted Decision Trees for efficient and accurate predictive modeling	[76]
Enconder-Decoder (ED) [48]	NN architecture consisting of an encoder and decoder, trained to learn a compressed representation of input data by minimizing the reconstruction error between input and output	[63]
GAN [77]	Deep learning framework consisting of two neural networks, the generator and the discriminator, engaged in a minimax game. The generator synthesizes data while the discriminator distinguishes between real and generated samples, aiming to achieve equilibrium in generating realistic data distributions	[39]
GRU [78]	Type of RNN, designed to capture long-range dependencies in sequential data, featuring simplified memory cells and gating mechanisms for efficiency in training	[57, 58, 63, 79, 80]
k-Means [81]	Clustering algorithm that partitions data into K clusters based on similarity, iteratively adjusting cluster centroids until convergence	[41, 72, 74]
k-NN [82]	Lazy supervised learning method where a data point is classified by a majority vote of its k nearest neighbors.	[53]
LSTM [83]	RNN designed to capture long-term dependencies in sequential data by utilizing specialized memory cells and gating mechanisms	[9, 39, 42, 43, 47, 49, 57, 58, 60–63, 63, 69, 79, 80, 84–97]
MARS [98]	Statistical method for non-linear regression analysis, employing piecewise linear segments to model complex relationships between multiple predictor variables and a response variable.	[72]
MLP [99]	NN with multiple layers of interconnected neurons, including an input layer, one or more hidden layers, and an output layer. It utilizes backpropagation for supervised learning.	[46, 47, 53, 63, 73, 85, 95, 97, 100–103]
OPENML [104]	Technique in machine learning that efficiently prunes irrelevant neurons from extreme learning machines to enhance model performance and reduce computational complexity	[72]
Random Forest (RF) [105]	An ensemble learning method in machine learning, consisting of multiple decision trees during training, resulting in improved accuracy and reduced overfitting through the aggregation of predictions.	[41, 47, 71, 106]
RNN [107]	Process sequential data by retaining information from previous inputs, making them suitable for tasks involving sequences such as time series prediction and natural language processing.	[46, 108]

Method	Short Description	Papers in this review
SVM [109]	Supervised ML algorithm that constructs a hyperplane in high-dimensional space to classify data points by maximizing the margin between different classes while minimizing classification error.	[58, 62, 63, 85, 101, 110, 111]
Transformer [112]	NN architecture based on self-attention mechanisms, enabling parallel processing of sequential data by capturing long-range dependencies without recurrent connections, yielding significant advancements in various natural language processing tasks	[97]
XGBoost [87]	Gradient boosting algorithm that efficiently handles various regression and classification tasks by sequentially adding weak learners, employing regularization techniques to prevent overfitting	[45, 73]

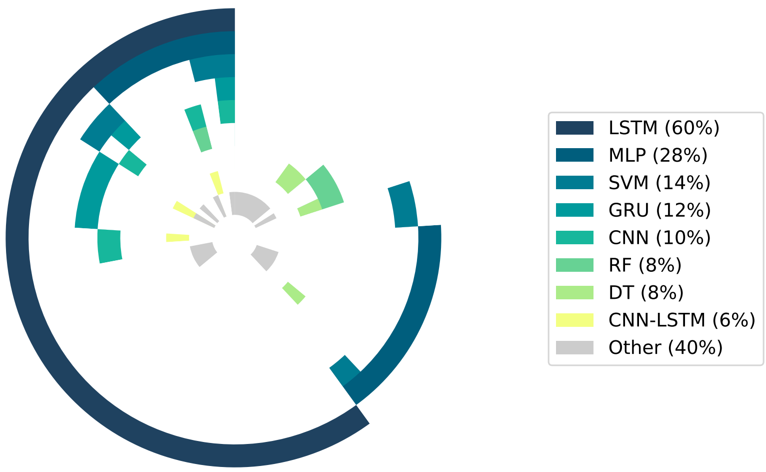

Figure 7 Frequency of machine learning (ML) methods for hydrological modeling of flash floods.

3.4 What are the minimum and maximum lead times and what temporal resolution have scientists used to investigate flash flood forecasting?

The lead time values ranged from 5 minutes [45] to 720 hours [49]. Most sub-hourly predictions utilized multiple variables for training, typically a combination of water level and rainfall [45–47, 84, 89, 91, 100, 103]. A mix of hourly rainfall and discharge was primarily used to forecast lead times beginning at 1 hour and extending to a maximum of 720 hours (e.g., [49]). The majority of studies applying LSTM methods projected discharge for lead times ranging from 1 to at least 6 hours [9, 42, 43, 47, 49, 61, 85].

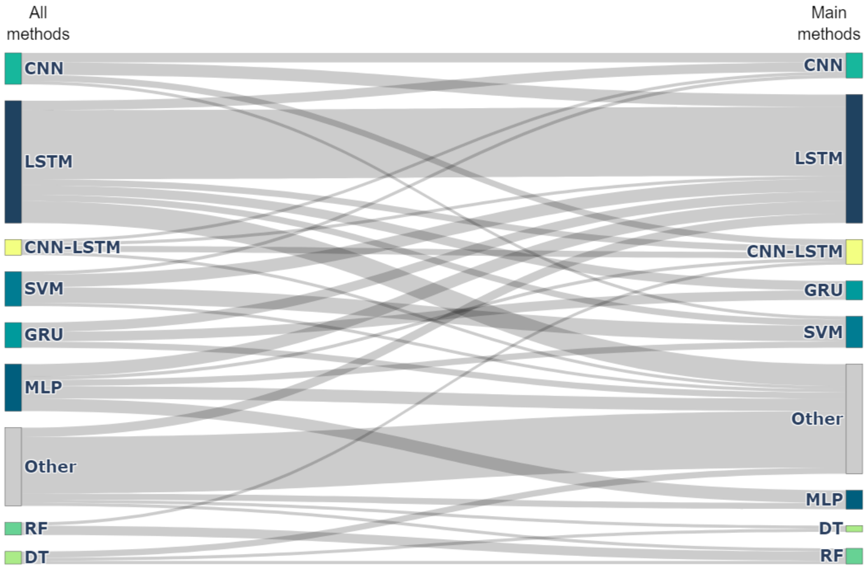

Figure 8 Proportion of all mentioned machine learning (ML) methods (left) and the main methods of each selected paper (right). A connection (gray line) from a method on the right to a method on the left means that those methods were compared 236 in the same paper - and the method from the right in this connection was one of those with the best performances in that paper.

3.5 Is remote sensing commonly used in machine learning (ML) hydrological models?

Despite being a common data source in many environmental studies and applications [74], remotely sensed data were applied in only seven papers (14%) (Figure 9). This limited usage may be due to the coarse spatial resolution often associated with meteorological products (e.g., precipitation and other environmental descriptors) derived from remote sensing data, as well as uncertainties related to their estimates. Additionally, the frequent unavailability of meteorological RADAR sensors may further contribute to this limited use. Consequently, studies might favor or depend on other data sources, such as ground-based measurements, hydrological models, or historical flood records. Lastly, the temporal resolution of remotely sensed data may not align well with the temporal dynamics of flash floods, which necessitate high-frequency data for accurate modeling.

However, while not widely utilized in the literature, it is important to emphasize that remotely sensed data, particularly those acquired by RADAR sensors, can offer valuable insights and support for ML-based approaches aimed at predicting flash floods [113].

3.6 Data availability

Among the reviewed articles, only 10% of them made the data used in the research publicly available ([55, 60, 72, 84, 85], while 90% of them did not share the data (Figure 9). Although it is essential to respect the data confidentiality policies of companies and institutions, this result is concerning as it hinders the ability to replicate and validate findings. Furthermore, it limits collaborations within the scientific community that could advance research in this field. Lastly, data sharing accelerates the pace of discovery and its benefits to society.

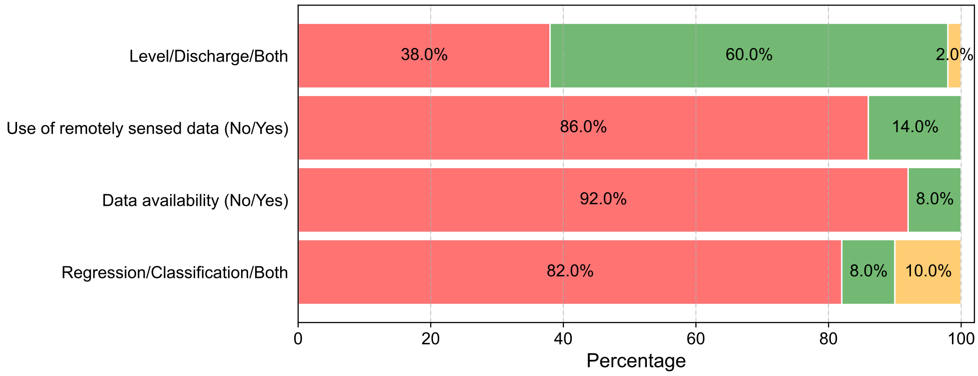

Figure 9 Ratio of the 50 articles that (i) presented water level, discharge, or both as output; (ii) used remotely sensed data; (iii) made data available; and (iv) applied regression, classification, or both

3.7 What is the most common problem: regression or classification?

Regression is the most common method for predicting flash floods, as indicated by the selected papers. As shown in Figure 9, 41 out of the 50 articles utilized at least one regression algorithm to forecast flash floods. Among these, four articles also incorporated a classification algorithm to address this issue. Furthermore, five articles employed both regression and classification algorithms to predict flash floods.

The dominance of regression algorithms can be explained by the fact that the variable of interest, i.e., the output data, is continuous in most of the articles included in this review. Basically, regression analysis is an ML approach that aims to predict the values of continuous output variables using input variables.

4 Main findings and open questions

This SLR identified a significant increase in the number of papers published considering ML methods for flash flood modeling. Out of over 800 papers, 50 were selected that aligned with the scope of the SLR. Most of the studies examined focus on regions in China, the US, and the Republic of Korea. Rainfall and discharge data emerge as the predominant input variables, and while discharge is the main output, compatible with physical-based models. 60% of the studies employ the LSTM method as one of the methods. Remotely sensed data are utilized in only 14% of the reviewed studies. Unfortunately, only 10% of the selected papers make their data publicly available. Lastly, regression is the primary problem addressed by these papers.

One of the major challenges in real-time flash flood forecasting is the inherent trade-off between forecast lead time and accuracy. In this regard, the reliability of early warnings can be compromised by systematic biases in rainfall forecasts, including the underestimation of extreme event intensity, errors in spatial placement, and temporal shifts in predicted rainfall. Several ML-based approaches can help mitigate these issues. Some of them are outlined below: (i) CNN can be used for downscaling numerical forecasts to obtain more accurate rainfall estimates with improved spatial resolution and to correct systematic error patterns; (ii) RNN and LSTM can be trained to learn corrections based on historical patterns of forecast errors, adjusting predicted rainfall to better match observations; (iii) MLPs, Random Forests, and XGBoost can be trained to estimate actual streamflow from biased rainfall forecasts, thereby reducing the impact of errors in the early detection of flash floods; and (iv) incorporating outputs from an ensemble of weather models into ML models can help reduce systematic bias and improve forecast reliability. Such integration of ML models into early warning systems offers a promising pathway to improving both the lead time and accuracy of flash flood alerts by mitigating biases in rainfall forecasts.

ML methods appear to be robust in predicting flash floods. Their data-oriented nature allows them to implicitly adapt to various input data sources, such as rain gauges, weather radar estimates of rainfall, water levels, or discharges. Additionally, ML methods offer a low processing cost for hydrological modeling. For example, a neural network may require a few hours for the training and validation phases, but once trained, the resulting model operates quickly enough to meet real-time demands within minutes or even seconds.

The following presents some open questions in ML modeling for flash floods, primarily regarding feature selection, uncertainty propagation, physically-inspired approaches, and open data sharing. Feature selection is the process of choosing the set of variables to be used as input in an algorithm. It is a widely adopted data preprocessing step in ML. In addition to enabling faster algorithms, it can also provide a better understanding of the underlying physical processes being modeled [114]. Feature selection has been applied in various studies of streamflow forecasting. In [115], a comparison of eight filter-based feature selection methods is performed for monthly streamflow forecasting. In [116], within the context of daily streamflow forecasting, a comparison is made between the feature selection ability of a hydrologist and that of different model structures that select automatically. However, despite the work already performed, more comparative studies on the application of feature selection for hourly streamflow prediction still need to be conducted, which may be further explored.

ML models could also help interpret and identify flash flood events, where a consensus for their identification remains an open question among the scientific community. For instance, [117] and [118] applied explainable ML methods (e.g., using SHAP -

SHapley Additive exPlanations - values) through input data features as a scalable approach to identify flash flood events across different spatial and temporal scales. In fact, more DL and ML could potentially be used not only to forecast flash flood events but also to improve their identification through time series of high-resolution basin attribute datasets. Methods such as F-IDF [11] could be enhanced by ML and DL models by combining spatially distributed static attributes (e.g., terrain slope) with dynamic features (e.g., rainfall and streamflow) as a potential approach to identify flash flood frequencies for regional, continental, and global extents.

The uncertainty analysis for hydrological models remains an important open question. The complex nature of modeling real-world hydrological processes, particularly flash floods, presents a persistent challenge. Understanding and quantifying the uncertainties associated with input and calibration data, model structural elements, and parameters is essential. These uncertainties not only affect the reliability of predictions but also influence decision-making processes for flash flood forecasting. A recent review of hydrological model uncertainties suggests that this issue is still in its early stages and requires further exploration and investigation [119]. Recent research has recognized the significance of this issue [120], but more is needed.

Recently, new mesh-free approaches have emerged with the help of ML methods that integrate available observations and compute surrogate solutions for nonlinear partial differential equations (PDEs), such as the Saint-Venant equation related to hydraulic problems [121, 122]. For instance, [123] established a physics-informed ML (PIML) model to combine the predictive capabilities of ML algorithms with the understanding of hydrological processes in physics-based models. A physics-informed learning algorithm, such as physics-informed neural networks (PINN), can solve PDE using feed-forward neural network architectures and incorporate physical laws that represent spatial and temporal changes through computational methods for automatic differentiation [124]. Many challenges remain in ML algorithms for hydrology, including black box models and surrogate models, where the objective function is approximated by optimizing the model's hyperparameters to achieve optimal solutions. Therefore, there is a pressing need to generate mathematical and computational knowledge of substitute modeling related to physical phenomena and data observations, which may yield promising results as a support tool for hydrological studies in watersheds at various temporal and spatial resolutions.

Given the vast diversity of ML methods for hydrological modeling, as well as the various areas of study and climates, comparing and ranking these methods presents a challenge. As a result, there is an increasing demand for open data sharing, which involves making publicly available standard datasets related to specific test cases of hydrological forecasts.

5 Getting evidence into practice

The application of ML approaches in flash flood forecasting is promising. However, to transform this theoretical potential into practical products and applications and maximize its impact, a series of actions involving collective efforts must be undertaken. In this context, some recommendations are outlined below:

Integration of ML into early warning systems: Integrate ML models into early warning systems, as these models can be updated in real-time with hydrological, meteorological, and satellite data to identify patterns indicative of flood occurrences and issue alerts with a better balance between lead time and assertiveness. Close cooperation is essential among ML developers, specialists (e.g., meteorologists and hydrologists), and civil defense agents in monitored risk areas to ensure that alerts remain accurate and interpretable.

Development and dissemination of benchmarks: Establish standardized benchmarks derived from diverse datasets and realistic scenarios, providing them to the scientific community for (i) assessing the effectiveness of developed ML solutions, (ii) ensuring their reliability and practical applicability, and (iii) promoting fast innovations in the field.

Publications and reviews focused on case studies: Publications showcasing successful case studies provide valuable insights into the challenges encountered and the strategies employed to overcome them. This can bolster the confidence of other researchers and practitioners in ML approaches and offer practical guidance for implementing these solutions in their contexts.

Multidisciplinary collaboration and scientific events: Organizing events such as workshops, seminars, and scientific conferences that bring together experts in AI, hydrology, disaster management, and public policy encourages exchange and collaboration among these professionals. This is essential for developing and implementing integrated solutions that promote innovations in flood forecasting, aligned with social and environmental needs.

Lastly, the selection of keywords determines which papers are eligible for inclusion in the analysis. In this study, only papers containing the keywords "artificial intelligence", "machine learning", or "deep learning" were considered. This choice results in the exclusion of some relevant papers on flash flood forecasting that apply traditional statistical methods but were not associated with ML or AI by their authors, such as [125, 126]. Future systematic reviews on flash flood forecasting may explicitly consider statistical and physically based methods.

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Author contributions

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Conflicts of interest statement

The authors declared no potential conflicts of interest with respect to the research.

Data availability statement

All data used in this work can be accessed at https://github.com/rogerionegri/iFAST.

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