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

Leonardo B. L. Santos[a,d,f,*], Luiz F. Satolo[a,d], Ricardo S. Oyarzabal[a], Elton V. Escobar-Silva[a,d], Michael M. Diniz[b], Rogério G. Negri[c], Glauston R. T. Lima[a], Stephan Stephany[d], Jaqueline A. J. P. Soares[a,d], Johan S. Duque[d,e], Fernando L. Saraiva Filho[f], Luiz Bacelar[g]

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Abstract

Background: 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 1,217 papers published until January 2024 and indexed in Web of Science, SCOPUS/Elsevier, Springer/Nature, or Wiley databases, we selected 53 for detailed analysis, following the PRISMA

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guidelines. The inclusion/exclusion criteria removed reviews, retractions, and papers that were not in the scope of this SLR and included only papers with time resolution coarser than 12 hours. Data about forecasting horizon, area, method and input were extracted from each study to identify which ML techniques and model designs have been 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 studies focus on regions in China (36%) and the United States (11%). Of the total of selected papers, more than 90% 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 half of the papers. Notably, almost 60% of the studies utilize the long short-term memory (LSTM) method. A strong result of this analysis is that no one method always performs better than any other. Unfortunately, less than 10% of 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, runoff, disasters

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GLOSSARY

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

1. Introduction

Flash floods are one of the most common types of natural disasters around the world Gourley et al. (2013); Georgakakos et al. (2022). They are defined as a fast rise of water level (0-12h) often triggered naturally by heavy rainfall Bucherie et al. (2022), quick snowmelt Yan et al. (2023), or induced by dam and levee breaks Yang et al. (2020). Since the triggering events usually occur on a small spatiotemporal scale, flash floods are predominant in urban areas with steep terrain or poor drainage systems, especially in regions prone to severe weather events Li et al. (2022). Smaller and steeper watersheds respond more rapidly to intense precipitation, resulting in a shorter time lag between the onset of heavy rain and the rise of water levels or river discharge, which may provide less warning time to residents and emergency responders Bucherie et al. (2022). In the face of climate change, the most likely scenario is that heavy rainfall events will become more frequent, consequently increasing the occurrences of flash floods in many susceptible watersheds Li et al. (2022).

Despite the advances in physically-based hydrological models Clark et al. (2017), such models are still typically applicable for flood forecasting in larger watersheds with slower responses and 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 rainfall accumulated volumes or weather numerical models to forecast precipitation at short lead times Georgakakos et al. (2022). The increased availability of hydrological observed data (e.g., water level and discharge) led to a growth in the use of data-driven hydrological models, where time-series of river level or discharge are forecasted without the need of knowing watershed-related physical parameters Tripathy and Mishra (2024). Given that good quality observed data is available, data-driven models can be more accurate in predicting river dynamics response, demanding less computational time and calibration needs than physically-based hydrological models Ng et al. (2023).

Artificial Intelligence (AI) is a broad research field that involves the design of systems based on computer programs capable of emulating human intelligence and thought processes to perform tasks such as reasoning, learning,

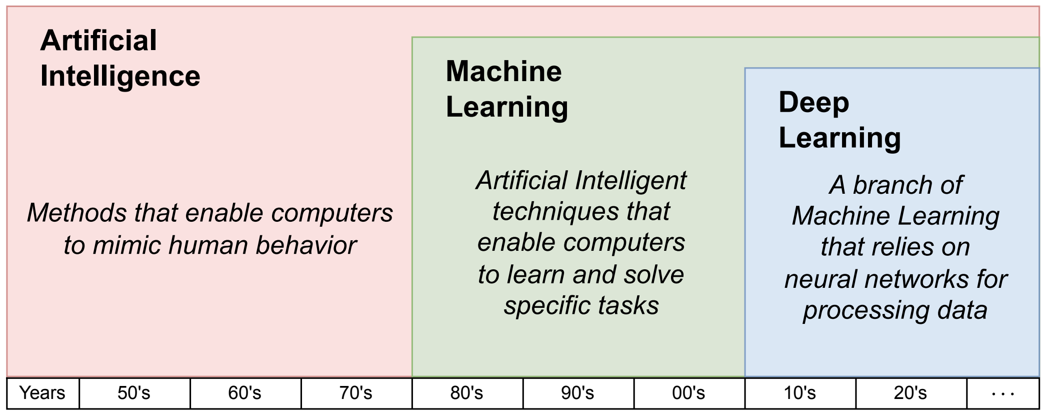

Figure 1: Artificial Intelligence trend towards Deep Learning for hydrological forecast/prediction along the years

interacting adaptively with the environment, and making decisions without the need for specific instructions. Among the possible approaches to designing AI systems, the most prominent is the use of Machine Learning (ML) techniques, which, generally speaking, are founded on the concept of learning directly and only from data. It is worth noting that the great momentum that AI has achieved in recent years can be largely attributed to advancements in the predictive performance of ML techniques, mainly using Deep Learning (DL) - see Figure 1.

As a consequence of the remarkable growth of ML methodologies in hydrological modeling, there has emerged a need for periodic literature reviews aimed at delineating the significant advancements and challenges within this research area. In 2014, a seminal contribution to this domain was presented by (Deka et al., 2014), wherein the researchers conducted a comprehensive examination of the contemporary advancements and prospective utility of

Support Vector Machine (SVM) techniques within the realm of hydrology.

In the subsequent year, Yaseen et al. (2015) investigated the utilization of ML for stream-flow forecasting spanning from 2000 to 2015. The research revealed that over the years under examination, ML methods have exhibited substantial advancements in the domain of hydrological forecasting and simulation, effectively capturing complex information in the data that the previous methods were not capable of.

Since 2021, there has been a substantial increase in the publication of review articles focused on applying ML within the field of hydrology. Notably, we draw attention to the work by Zounemat-Kermani et al. (2021), wherein the authors investigated the progress in employing ensemble methods across diverse hydrological application domains. Their findings suggest a general trend of superiority in performance compared to conventional machine learning models Zounemat-Kermani et al. (2021).

In the runoff context, a comprehensive examination is presented in Mohammadi (2021), where the authors assessed the specific utilization of Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Artificial Neural Networks (ANN), and SVM for runoff simulations. The primary objective of this review was to elucidate the principal merits and limitations inherent to each of these methodologies. Other reviews on the use of ML in hydrological contexts can be found in (Lange and Sippel, 2020; Mosaffa et al., 2022; Mashala et al., 2023).

With the progress of scientific repository search tools, the prospect of methodically organizing and reproducing literature review protocols has emerged, culminating in the establishment of a paradigm known as *Systematic Reviews*

Pati and Lorusso (2018). In Ardabili et al. (2020), a systematic review is conducted about the state-of-the-art ML and DL methods in the prediction of hydrological processes, climate changes, and earth systems. Other more general systematic reviews involving hydrology can be found in Leitzke and Adamatti (2021).

Given the foregoing, the present paper conducts a Systematic Literature Review (SLR) to enhance our comprehension of the research landscape on ML applications for modeling flash floods.

2. Methodology

To the best of our knowledge, this represents the inaugural comprehensive literature review on ML models for hydrological forecasting, explicitly focusing on rapid processes like flash floods. We outlined the scope of the review to tackle different key questions regarding flash flood forecasting while maintaining conciseness.

This review covers articles on ML and hydrological models through a deep search in large scientific databases, for this purpose, it adopts the process suggested by Page et al. (2021b,a), 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 processes carried out, PRISMA 2020 checklist, is presented in `https://github.com/rogerionegri/iFAST`.

Our search strategy employed keywords relevant to the research questions, utilizing Boolean operators. We used "OR" to encompass synonyms and alternative spellings and "AND" to connect primary terms with secondary ones (see BOX 1).

This review considered articles published in peer-reviewed journals in the English language until December 2023. The following databases were considered: Web of Science, SCOPUS/Elsevier, Springer/Nature, and Wiley. The searches took into account the paper titles, keywords, and abstracts. No limit was set for the number of articles returned in the query. Also, we included 20 other papers based on previous knowledge of the literature.

BOX 1: Combination of keywords used in the review

TIER		
1: machine learning	2: hydrology	3: fast response

artificial intelligence OR machine learning OR deep learning

hydrology OR hydrological model OR hydrological forecast OR flood OR rain-runoff

fast response OR fast dynamic OR rapid response OR rapid dynamic OR short lead time OR short term forecast

In the first screening process, we removed duplicates. A table with all these 808 papers is presented in `https://github.com/rogerionegri/iFAST`. In the second one, we removed reviews, retractions, and papers that were not in the scope of the review for addressing mainly topics such as rainfall forecast, groundwater forecast, flood mapping, coastal flooding, tsunami forecast, or for dealing with data with time resolution coarser than 12 hours.

So, the final set of papers for this review had 53 papers.

Considering this final set of papers on ML models for flash floods, we analyzed different characteristics. A datasheet with all the 53 selected papers and their attributes is presented in `https://github.com/rogerionegri/iFAST`. A summary of the attributes considered in this study is presented in Table 1.

The PRISMA diagram of this systematic review can be seen in Figure 2.

3. Results and Discussion

Figure 3 displays the number of publications, both yearly and cumulatively, related to the topic of this review. It is evident that there has been a rise in recent years, particularly after 2021, and there has been a huge number of papers in the last year. Such growth is possibly due to either the worsening of flash flood occurrences due to recent climate changes or the availability of machine learning methods proposed recently.

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 it most common to find research related to ML and flash floods?

Figure 5 depicts a spatial representation of the number of studies conducted in different areas of the globe. This representation allows us to identify that the revised studies cover 21 countries distributed throughout Africa,

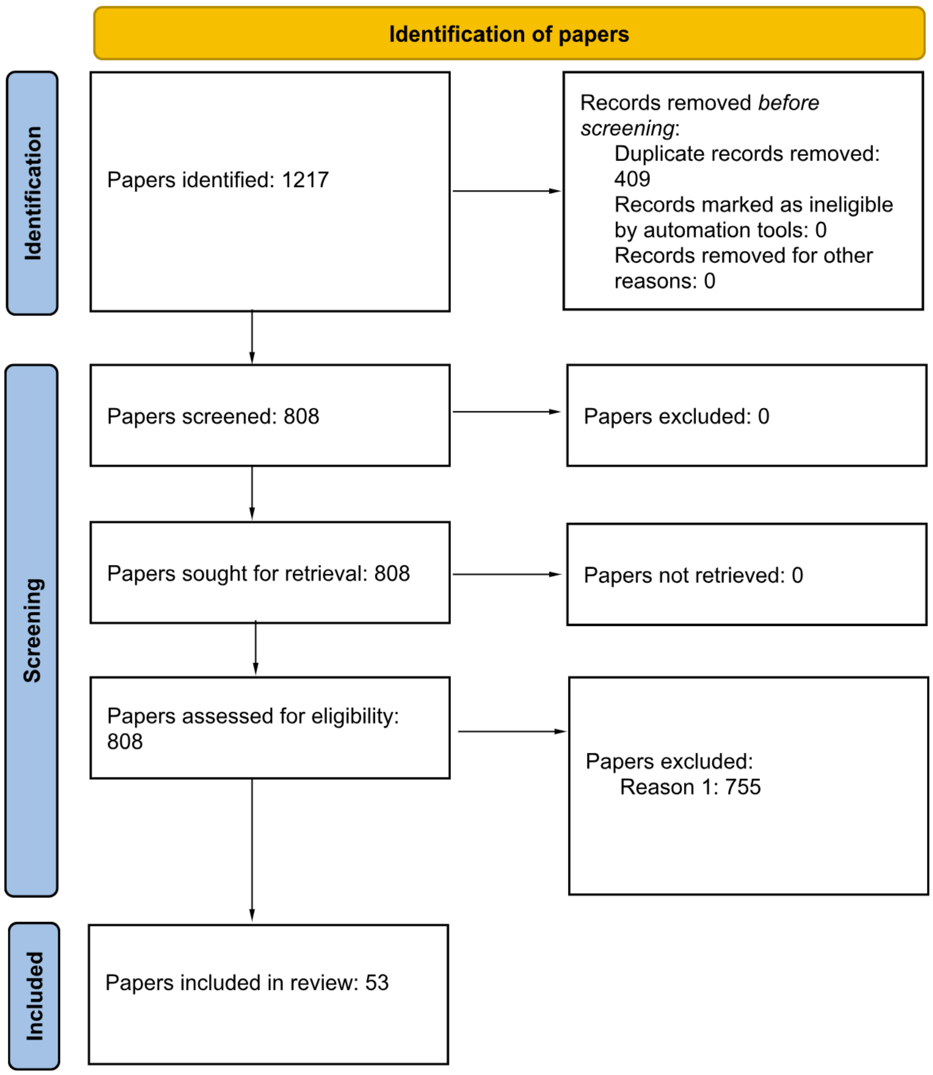

Figure 2: PRISMA 2020 workflow diagram.

Table 1: Summary of attributes observed in the reviewed papers.

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

Asia, Europe, and North and South America. Most of the studies were carried out in areas located in China and the United States (U.S.).

This scenario must be a reflection that China and the U.S. are among the most flood-experienced countries in the world, alongside India, Indonesia, the Philippines, and Brazil Hu et al. (2018c). China is the country most severely threatened by flood disasters globally, with damages from such events be-

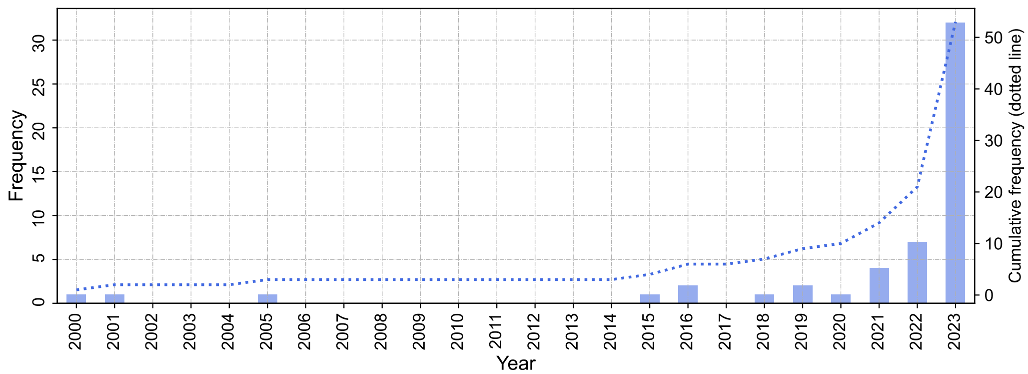

Figure 3: Absolute and cumulative number of publications about Machine Learning applied to flash floods per year.

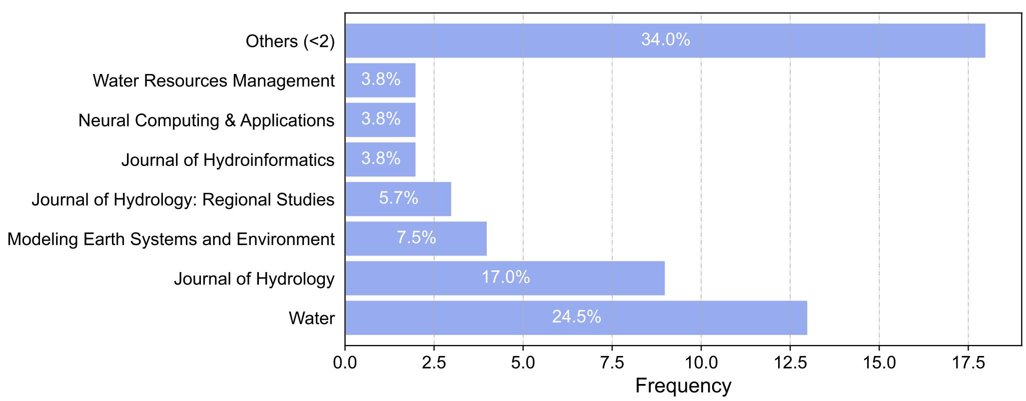

Figure 4: Frequency of articles using Machine Learning for flash flood hydrological modeling by journal.

tween 1990 and 2017 accounting for approximately 10% of the world's total Kundzewicz et al. (2019). Flash floods, in particular, are widely recognized as a significant cause of human casualties and economic losses in China Liu et al. (2020); Zhao et al. (2022). From the American perspective, flash floods result in the highest number of casualties among various flood events in the U.S. Ashley and Ashley (2008); Terti et al. (2017). 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 Khouakhi et al. (2017).

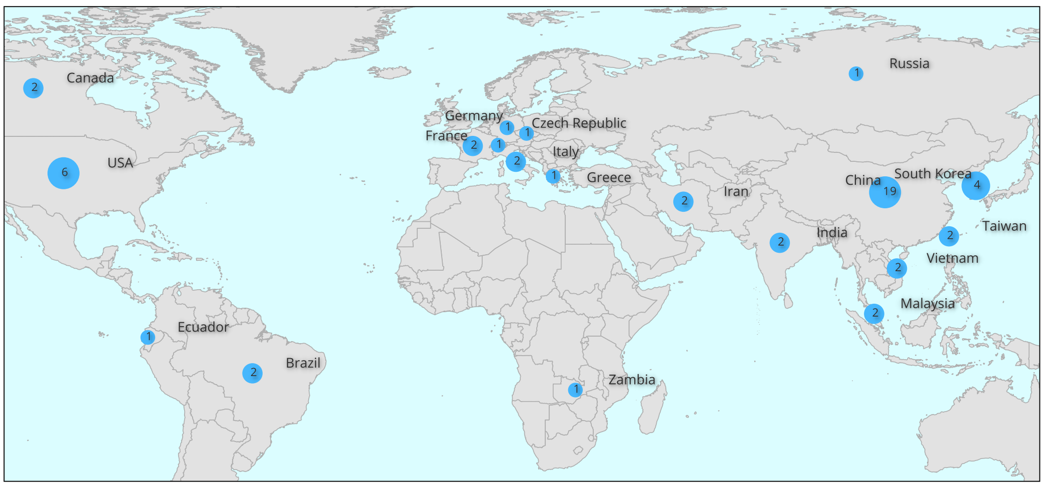

Figure 5: Frequency of articles applying Machine Learning to flash floods according to country application.

3.2. Which input and output data are most commonly used in ML models for flash floods?

Among the 53 selected articles, rainfall is the most commonly used input variable, appearing in 47 studies ($\approx$ 89%). Discharge data is used in 31 studies ($\approx$ 58%), and water level data is used in 22 studies ($\approx$ 42%).

Of the total of 53 articles selected, 48 of them used as input data just one or an exclusive combination of the following measurements: flow, rainfall, and water level. The Venn diagram in Figure 6 summarizes the input data used in these 48 studies.

Notably, only 4 papers ($\approx 8\%$) combined rainfall, water level, and discharge data simultaneously. Additionally, 4 studies used only rainfall data, 3 studies used only water level data, and 2 studies used only discharge data.

It is worth noting that flow and precipitation are the most common combinations in these studies – and are also appropriate for physically based models. Studies that exploit water level data in ML applications for flash flood prediction have great potential, as acquiring water level data is often simpler than acquiring discharge data.

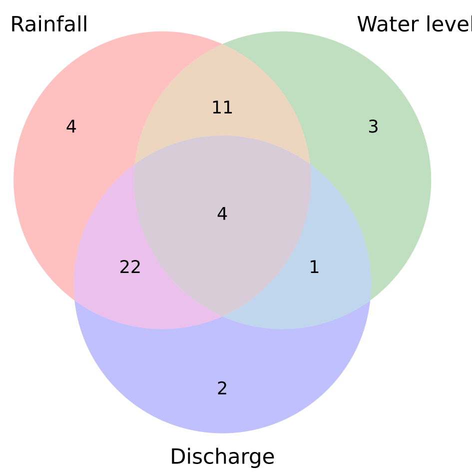

Figure 6: Veen diagram of the types of input data of the revised papers.

3.3. What is the most used ML method for modeling flash floods?

Table 2 presents a list of the most used ML methods for modeling flash floods. It also shows a short description of each method and the respective papers in which they are presented as one of the main methods (methods with best performance).

Furthermore, the frequency of each ML method applied for hydrological modeling is shown in Figure 7. It is possible to see that the LSTM was the most used method, appearing as on the the methods in almost 60% of the works, followed by MLP, used in almost 30%. The revised studies also used tree-based methods (Decision Trees or Random Forests) and the Support Vector Machine (SVM), which were used in $\approx 15\%$ and $\approx 13\%$ of the papers, respectively. Other methods were employed, like K-Means, K-Nearest Neighbors, Extreme Machine Learning, Particle Swarm Optimization, and Fuzzy-based methods, on a minor frequency.

Figure 8 shows a comparison between all ML methods presented in the articles - including methods for comparing results and the main methods: the methods with the best performance in each paper. It is possible to note that LSTM is used and performed as one of the best methods in this set of papers. A strong result of this analysis is that no one method always performs better than any other. So, it is critical to try different methods in each research problem to find out what is most appropriate in each case study.

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

Method	**Short Description**	**Papers in this review**
LSTM Graves and Graves (2012)	RNN designed to capture long-term dependencies in sequential data by utilizing specialized memory cells and gating mechanisms	Song et al. (2019a) Hu et al. (2018a) Zhou et al. (2023a) Chiacchiera et al. (2022) Yan et al. (2021) Han and Morrison (2022a) Li et al. (2021a) Devi et al. (2022a) Li et al. (2021b) Ho et al. (2022) He et al. (2023b) Huang et al. (2023a) Dai et al. (2023a) Liu et al. (2023) Dehghani et al. (2023a) Tan et al. (2023) Xu et al. (2023) Koutsovili et al. (2023a) Guo et al. (2023a) Cui et al. (2023) Zhang et al. (2023b) Zhang et al. (2023a) Wang et al. (2023c) Huang et al. (2023b) Guo et al. (2023b) Yang et al. (2023) Weng et al. (2023) Le et al. (2023) Kim et al. (2023) Moon et al. (2023) Chen et al. (2023)
DANN Sabour et al. (2017)	The Dynamic that adjusts the structure of the neural network during training	Banihabib et al. (2015)

Method	Short Description	Papers in this review
MLPRumelhart et al. (1986)	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.	Toth et al. (2000) Kim and Barros (2001) Zhou et al. (2023a) Saint-Fleur et al. (2023a) Han and Morrison (2022a) Shirali et al. (2020) Belyakova et al. (2022) Tan et al. (2023) Xu et al. (2023) Lee (2023) Huang et al. (2023b) Saint-Fleur et al. (2023b) Santos et al. (2023a) de Lima et al. (2016a)
k-NN Fix (1985)	Lazy supervised learning method where a data point is classified by a majority vote of its k nearest neighbors.	Toth et al. (2000)
ANFIS Jang (1993)	Hybrid system that combines fuzzy logic and NN techniques for adaptive modeling and inference.	Nayak et al. (2005)
XGBoost Chen and Guestrin (2016)	Gradient boosting algorithm that efficiently handles various regression and classification tasks by sequentially adding weak learners, employing regularization techniques to prevent overfitting	Sanders et al. (2022a) Belyakova et al. (2022)
RNN Amari (1972)	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.	Saint-Fleur et al. (2023a) Wang et al. (2023c)
k-Means MacQueen et al. (1967)	Clustering algorithm that partitions data into K clusters based on similarity, iteratively adjusting cluster centroids until convergence	Adnan et al. (2021) Tang et al. (2023) Wang et al. (2023a)
PSO Kennedy and Eberhart (1995)	Stochastic optimization algorithm inspired by the social behavior of swarm, iteratively optimizing a problem by adjusting a population of candidate solutions based on each particle's movement towards the best-known positions.	Souza et al. (2022)
CNN LeCun et al. (1998)	Deep learning architectures adept at processing structured grid data, utilizing convolutional layers to learn hierarchical features automatically.	Zhou et al. (2023a) Chiacchiera et al. (2022) Huang et al. (2023a) Dehghani et al. (2023a) Huang et al. (2023b)

Method	Short Description	Papers in this review
Transformer Vaswani et al. (2017)	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	Xu et al. (2023)
Random Forest (RF) Breiman (2001)	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.	Zhou et al. (2023a) Erechtchoukova et al. (2016) Tang et al. (2023) Muñoz et al. (2023)
SVM Cortes and Vapnik (1995)	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.	Guo et al. (2023a) Wu et al. (2019) Han and Morrison (2022a) Shirali et al. (2020) Huang et al. (2023a) Langhammer (2023) Huang et al. (2023b)
CGBR Prokhorenkova et al. (2018)	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.	Guo et al. (2023a) Guo et al. (2023b)
GRU Chung et al. (2014)	Type of RNN, designed to capture long-range dependencies in sequential data, featuring simplified memory cells and gating mechanisms for efficiency in training	He et al. (2023b) Guo et al. (2023a) Zhang et al. (2023b) Huang et al. (2023b) Guo et al. (2023b) Le et al. (2023)
Conv-LSTM Shi et al. (2015)	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.	Zhou et al. (2023a) Deghani et al. (2023a) Guo et al. (2023b)
BMA Sun et al. (2021)	Statistical technique that combines Bayesian models in a temporal framework, considering changes in relationships between variables over time.	Zhou et al. (2023c)
Enconder-Decoder (ED) Hinton and Salakhutdinov (2006)	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	Huang et al. (2023b)

Method	Short Description	Papers in this review
ELGBDT Liu and Wu (2017)	An ensemble learning technique that combines the strengths of Extreme Learning Machines and Gradient Boosted Decision Trees for efficient and accurate predictive modeling	He et al. (2023a)
DSTGNN Diao et al. (2019)	Method for modeling dynamic spatiotemporal data, leveraging GNN to capture spatial dependencies and temporal dynamics efficiently	Yang et al. (2023)
GAN Goodfellow et al. (2014)	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	Weng et al. (2023)
DNN Robbins and Monro (1951)	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	Saint-Fleur et al. (2023b)
AE Hinton and Salakhutdinov (2006)	Neural network architecture designed for unsupervised learning that learns to encode input data into a latent representation and reconstruct it with minimal loss.	Devi et al. (2022a)
ARMA Whittle (1951)	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	Toth et al. (2000)
DT Das Gupta (1980)	A machine learning algorithm that recursively partitions data based on feature values to create a predictive model represented by a tree-like structure	Adnan et al. (2021) Belyakova et al. (2022) Erechtchoukova et al. (2016) Wang et al. (2023a)
MARS Friedman (1991)	Statistical method for non-linear regression analysis, employing piecewise linear segments to model complex relationships between multiple predictor variables and a response variable.	Adnan et al. (2021)
OPENML Miche et al. (2009)	Technique in machine learning that efficiently prunes irrelevant neurons from extreme learning machines to enhance model performance and reduce computational complexity	Adnan et al. (2021)

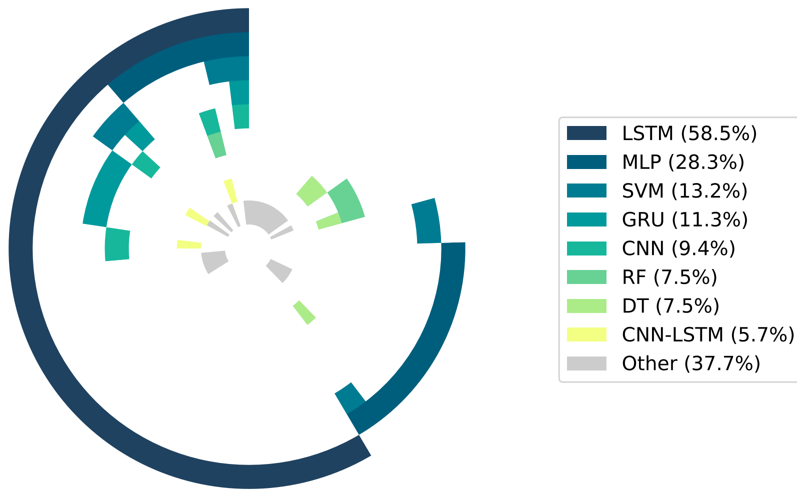

Figure 7: Frequency of Machine Learning methods for hydrological modeling of flash floods.

3.4. Which lead time (min and max) and temporal resolution have scientists used to investigate flash flood forecasting?

The lead times values varied from 5 minutes Sanders et al. (2022b) to 720 hours Devi et al. (2022b). Most sub-hourly predictions employed multiple variables for training, typically a combination of water level and rainfall Sanders et al. (2022b); Li et al. (2021c); Dai et al. (2023b); Koutsovili et al. (2023b); Zhou et al. (2023b); Saint-Fleur et al. (2023c); Santos et al. (2023b); de Lima et al. (2016b).

A combination of hourly rainfall and discharge was predominantly used to forecast lead times starting at 1 hour to a maximum of 720 hours (e.g., Devi et al. (2022b)). The majority of the studies that applied LSTM methods foretasted discharge for lead times from 1 to at least 6 hours Yan et al. (2023); Devi et al. (2022b); Zhou et al. (2023b); Han and Morrison (2022b); Song

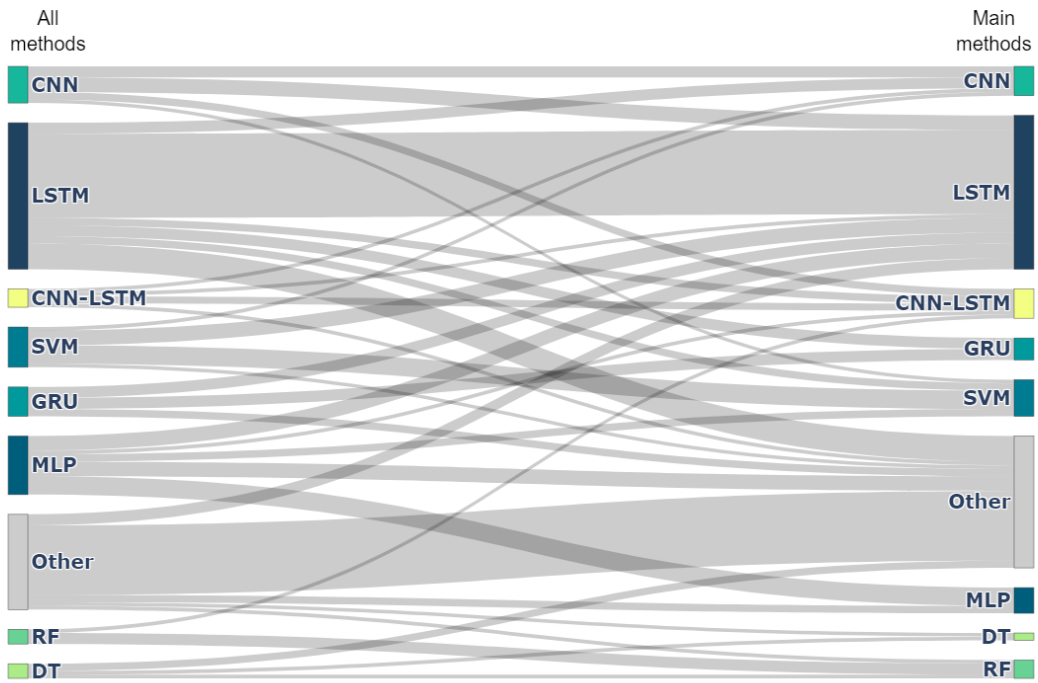

Figure 8: Proportion of all mentioned Machine Learning methods (left) and the main methods of each selected paper (right). A connection (gray line) from a method on the right to a method on the left means that those methods were compared in the same paper - and the method from the right in this connection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

et al. (2019b); Hu et al. (2018b); Dehghani et al. (2023b).

3.5. Is remote sensing widely used in ML hydrological models?

Despite being a common data source in many environmental studies and applications Wang et al. (2023b), remotely sensed data were observed in only 15.1% of the reviewed studies (Figure 9).

This limited usage may be attributed to the coarse spatial resolution typically 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 usual unavailability of meteorological RADAR sensors may further contribute to this limited use. Consequently, studies might prefer or rely on other data sources, such as ground-based measurements, hydrological models, or historical flood records. Additionally, the temporal resolution of remotely sensed data might not fit well with the temporal dynamics of flash floods, which require high-frequency data for accurate modeling.

However, although not well-exploited in the literature, it is worth highlighting that remotely sensed data, especially those acquired by RADAR sensors, may provide valuable data and support for ML-based approaches designed for flash flood prediction.

3.6. How many of the reviewed articles make the data available?

Among the reviewed articles, 13.2% made the data used in the research available, while 1.9% made the data partially available, and 84.9% did not make the data available (Figure 9).

While it is necessary to respect the data confidentiality policies of companies and institutions, this result is concerning as it reduces the possibility of replicating and validating results. Furthermore, it limits collaborations in the scientific community that could advance research in this field. Lastly, data sharing helps speed up the pace of discovery and its benefits to society.

3.7. What is the most frequent problem: regression or classification?

Regression is the main problem in the prediction of flash floods, according to the selected papers. As shown in Figure 10, 49 out of the 53 articles applied at least one regression algorithm to predict flash floods. Among them, 5 articles also applied a classification algorithm to tackle this problem. On the other hand, only 4 articles used classification algorithms to predict flash floods.

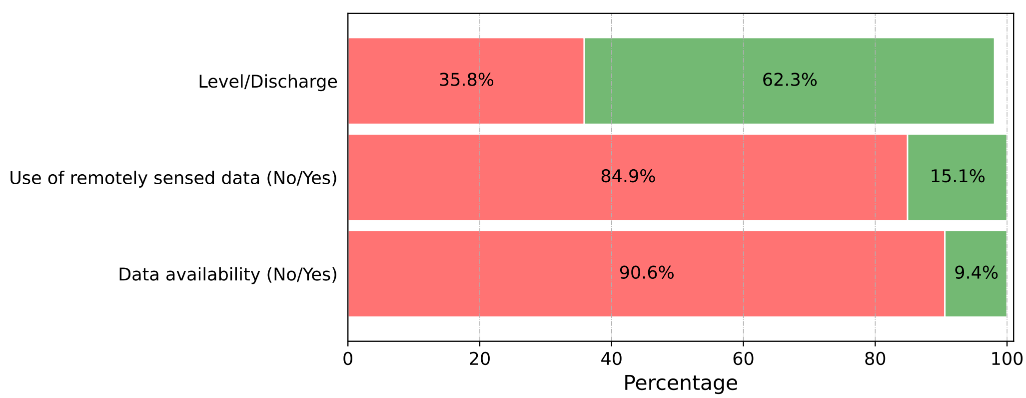

Figure 9: Ratio of the 53 articles that (i) presented water level, discharge, or both as output; (ii) used remotely sensed data; (iii) made data available; and (iv) applied regression, classification, or both.

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 value of continuous output variables using input variables.

4. Main findings and open questions

This SLR found a significant increase in the number of papers published considering ML methods for flash flood modeling. Of the over 800 papers, 53 articles were selected, which followed the scope of the SLR. Most of the

Figure 10: Supervised learning algorithms applied to flash flood prediction.

studies examined focus on the regions of China and the US. Rainfall and discharge data emerge as the predominant input variables, and discharge is the main output: compatible with physical-based models. Almost 60% of the studies employ the LSTM method as one of the methods. Remotely sensed data are utilized in only $\approx 15\%$ of the reviewed studies. Unfortunately, less than 10% of the selected papers make data available. Lastly, regression is the primary problem addressed by the papers.

ML methods seem to be robust for predicting flash foods. Due to their data-oriented nature, they implicitly adapt to different input data, such as rain gauges or weather radar estimates of rainfall, water legal or discharges, etc. Another advantage of ML methods for hydrological modeling is their low processing cost. For instance, a neural network may demand a few hours for the training and validation phase, but once trained, the resulting model is fast enough for real-time demands of a few minutes, even seconds.

It is worth highlighting some open questions in ML modeling for flash floods, mainly about 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 used technique in machine learning. In addition to providing faster algorithms, it can also provide a better understanding of the underlying physical process being modeled Guyon and Elisseeff (2003). Feature selection has been applied in a variety of studies of streamflow forecasting. In Ren et al. (2020), a comparison of eight filter-based feature selection methods is performed for monthly streamflow forecasting. In Moreido et al. (2021), in 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, even with 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.

The uncertainty analysis for hydrological models stands as an important open question. The complex nature of modeling real-world hydrological processes, particularly flash floods, presents an ongoing challenge. Understanding and quantifying uncertainties associated with input and calibration data, model structural elements, and parameters is critical. These uncertainties not only affect the reliability of predictions but also impact decision-making processes for flash flood forecasting. A recent review of hydrological model uncertainties indicates that this issue remains at an early stage and requires further exploration and investigation Moges et al. (2021). Brand new research recognized the significance of this issue Soares et al. (2024), but more is needed.

Recently, new mesh-free approaches have emerged with the help of ML methods that assimilate available observations and compute surrogate solutions of nonlinear Partial Differential Equations (PDE), such as the Saint-Venant equation related to hydraulic problems Willard et al. (2022); Sirignano and Spiliopoulos (2018). For example, Bhasme et al. (2022) established a Physics-Informed Machine Learning (PIML) model to combine the predictive ability of ML algorithms with the process understanding of physics-based models for hydrological processes. A physics-informed learning algorithm such as Physics-Informed Neural Networks (PINN) can solve PDE using feed-forward neural network architectures and including physical laws representing the spatial and temporal changes through computational methods for automatic differentiation Raissi et al. (2019). Many problems are still open in ML algorithms for hydrology contributions, such as the black box models or surrogate models where the objective function is approximated by optimizing the model's hyperparameters to get optimal solutions. There is a current need to generate mathematical and computational knowledge of substitute modeling related to physical phenomena and data observation, which may have promising results as a support tool for hydrological studies in a watershed at different temporal and spatial resolutions.

Considering the vast diversity of ML methods for hydrological modeling, as well as different areas of study with different climates, it would be challenging to compare and rank these methods. As a consequence, there is an appeal towards the use of open data sharing, making publicly available standard datasets related to specific test cases of hydrological forecasts.

5. Getting evidence into practice

The use of ML approaches in flood forecasting is promising. However, in order to convert this theoretical potential into practical products and applications and maximize its impacts, it is necessary to undertake a set of actions involving collective efforts. In this regard, some recommendations are outlined below:

Integration of ML into early warning systems: Integrate ML models in early warning systems because such models can be fed in real-time with hydrological, meteorological, and satellite data to identify patterns indicative of flood occurrences and issue alerts with a better compromise between lead time and assertiveness; it is essential to have close cooperation between ML developers, specialists such as meteorologists and hydrologists, and also civil defense agents from monitored risk areas to ensure that the alerts remain accurate and interpretable.

Development and dissemination of benchmarks: Creating standardized benchmarks based on diverse datasets and realistic scenarios and making them available to the scientific community for (i) evaluating the effectiveness of developed ML solutions, (ii) ensuring their reliability and practical applicability, and (iii) fostering rapid innovations in the field.

Publications and reviews focused on case studies: Publications highlighting successful case studies with valuable insights into the challenges faced and the strategies used to overcome them can reinforce the confidence of other researchers and practitioners in ML approaches and offer practical guidance for applying them as solutions in their particular contexts.

Multidisciplinary collaboration and scientific events: The organization of events such as workshops, seminars, and scientific conferences that bring together experts in AI, hydrology, disaster management, and public policy facilitates the exchange and collaboration among these professionals, which is essential for the development and implementation of integrated solutions that drive innovations in flood forecasting aligned with social and environmental needs.

The last topic to be highlighted is that, as in any systematic review, the set of keywords determines the papers eligible to be included in the analysis. In this study, only the papers containing the keywords “artificial intelligence” or “machine learning” or “deep learning” were considered. This decision has the penalty of leaving out some relevant papers about flash flood forecasting that apply traditional statistical methods but were not associated with machine learning or artificial intelligence by their authors, like Prakash et al. (2023) and Brito et al. (2023). Future versions of systematic reviews about flash flooding forecasting may consider explicitly statistical and physical-based methods.

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\textbf{Background}: 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.

\textbf{Methods}: Starting with more than 1,217 papers published until January 2024 and indexed in Web of Science, SCOPUS/Elsevier, Springer/Nature, or Wiley databases, we selected 53 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 with time resolution coarser than 12 hours. Data about forecasting horizon, area, method and input were extracted from each study to identify which ML techniques and model designs have been applied to flash flood forecasting.

\textbf{Results and Discussion}: There has been a notable increase in publications investigating ML techniques for flash flood modeling over the last few years. Most studies focus on regions in China (36\%) and the United States (11\%). Of the total of selected papers, more than 90\% 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 half of the papers. Notably, almost 60\% of the studies utilize the long short-term memory (LSTM) method. A strong result of this analysis is that no one method always performs better than any other. Unfortunately, less than 10\% of 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.

Highlights (3 to 5 bullet points (maximum 85 characters including spaces per bullet point)

To the best of our knowledge, this represents the inaugural comprehensive literature review on ML models for flash floods

This review adopts the PRISMA 2020 protocol

Of the total of selected papers, more than 90% used as input data just one or an exclusive combination of the following measurements: discharge, rainfall, and water level

No one method always performs better than any other in the selected papers

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 the work described has not been published previously.

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