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

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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 1,200 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 technique, and the type of outcome 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. We recommend integration into early warning systems, development and dissemination of benchmarks, publication of successful case studies, and multidisciplinary collaboration.

Keywords: artificial intelligence, flood forecasting, disasters, PRISMA

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	KNN	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	Enconder Decoder	XGBoost	Extreme Gradient Boosting
ELGBDT	Extreme Learning Machines and Gradient Boosted Decision Trees		

1. Introduction

Nearly 44% disasters worldwide have been associated with floods, and different types of floods account for 31% economic losses [1]. It is estimated that from 2000 to 2024 (until August), floods affected over 1.8 billion people and caused a global annual average economic loss of US $ 38.88 billion [2]. Worsening this situation, ongoing global climate change is expected to increase the frequency and magnitude of such events [3,4]. Flash floods are one of the most common types of natural disasters around the world [5,6]. Flash floods refer to a high peak discharge or a fast rise in water level (mostly <6 h) [7] often triggered naturally by heavy rainfall [8], quick snowmelt [9], or induced by dam and levee breaks [10]. 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 [4]. 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, which may provide less warning time to residents and emergency responders [8].

Hydrological models are used to study the hydrologic cycle, representing a part (or stage) of it [11]. There are many forms of hydrological models since they are designed to deal with different problems. These models consider various factors, such as catchment characteristics and the spatial and temporal variations in rainfall [12], which can explicitly describe flash flood behaviors. Therefore, they are essential tools for flash flood prediction and issuing timely warnings.

Despite the advances in physically-based hydrological models [13], 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 [5]. 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 [14]. 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 [15].

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, interacting adaptively with the environment, and making decisions without the need for specific instructions [16]. 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 [17]. 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.

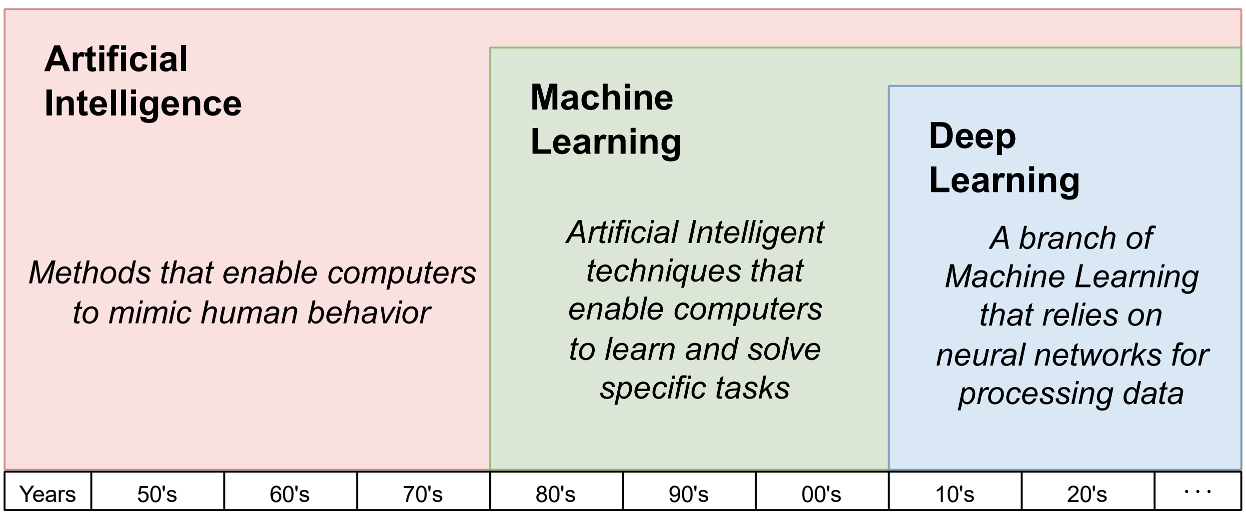

Figure 1. Artificial intelligence (AI) trend towards deep learning (DL) for hydrological forecast/prediction along the years.

As a consequence of the remarkable growth of ML methodologies in hydrological modeling, there has emerged a need for periodic literature reviews aimed to delineate the significant advancements and challenges within this research area. In 2014, a seminal contribution to this domain was presented by [18], 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, [19] investigated the utilization of ML for streamflow 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 [20], 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. In the runoff context, a comprehensive examination is presented in [21], 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 [22–24].

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* [25]. In [26], a systematic review is conducted about the state-of-the-art of 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 [27]. 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 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 [28,29], 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, the PRISMA 2020 checklist, is presented 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 structured into overarching concepts or tiers. We used "OR" to encompass synonyms and alternative spellings and "AND" to connect primary terms with secondary ones. It was 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.

In the first screening process, we removed duplicates. 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 6 hours. So, the final set of papers for this review had 50 papers. Considering this final set of papers on ML models for flash floods, we analyzed different characteristics. A datasheet with all the 50 selected papers and their attributes is presented at https://github.com/rogerionegri/iFAST. A summary of the attributes considered in this study is presented in Table 1.

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 publicly available
input data	input data used in the model (rainfall, water level, or discharge)
lead time (max)[h]	maximum forecast horizon
lead time (min) [h]	minimum forecast horizon
ML main method	type of ML method
model output data	level, discharge, or both
regression, classification, or both	the model predicts either a value or a class (category) for each input data presented to it, respectively
remote sensing	if the paper uses remote sensing data (radar or satellite)
temporal resolution (min)	temporal resolution of input data

Lastly, the PRISMA diagram of this systematic review can be seen in Figure 2.

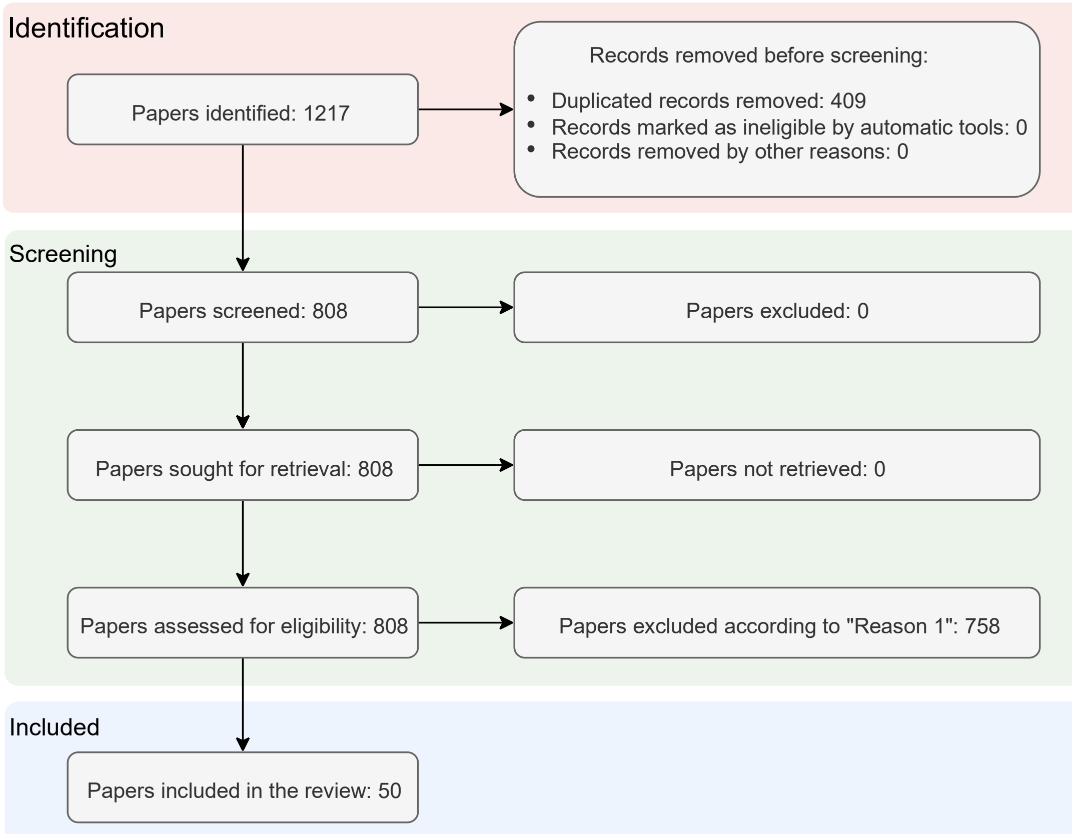

Figure 2. The PRISMA 2020 workflow diagram.

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 considerable increase in recent years, particularly after 2021, and there was published a huge number of papers in 2023. Such growth is possibly due to either the worsening of flash flood occurrences due to recent climate changes or the availability of ML methods proposed recently.

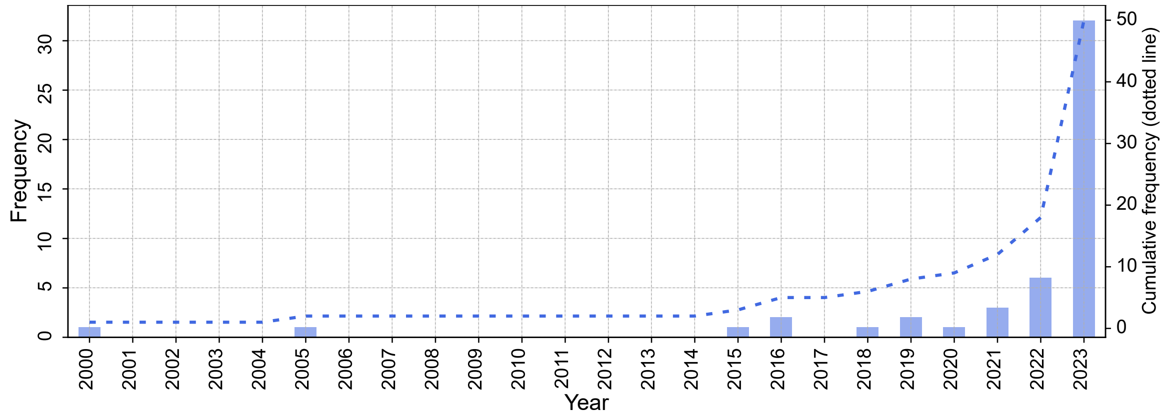

Figure 3. Absolute and cumulative number of publications about machine learning (ML) applied to flash floods per year.

The top seven journals encompass a diverse range of fields, from Hydrol1ogy 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.

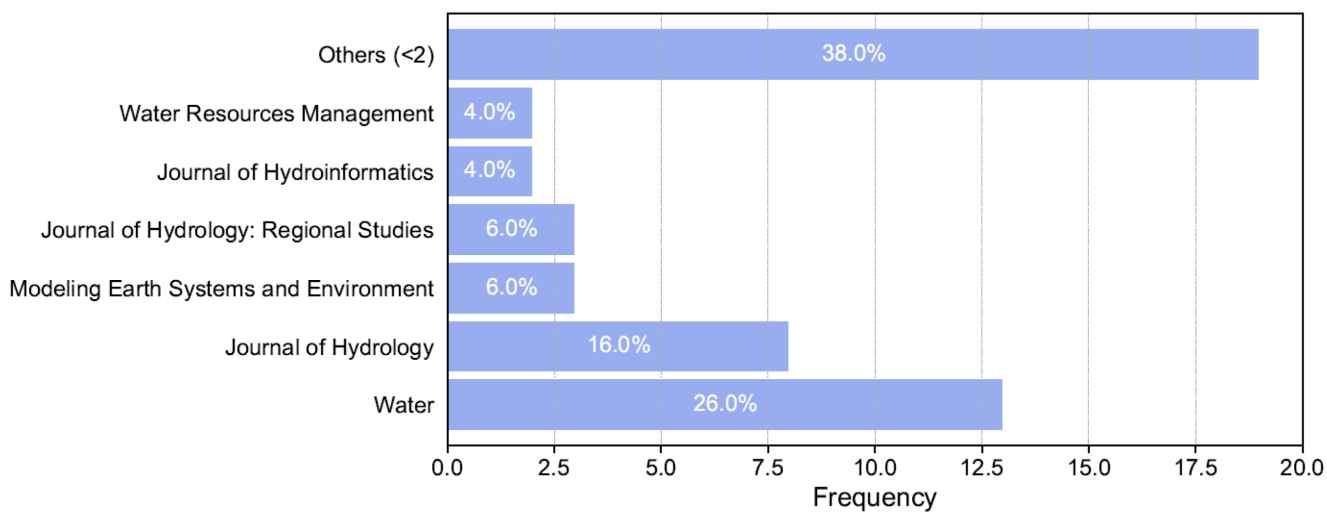

Figure 4. Frequency of articles using machine learning (ML) for flash flood hydrological modeling by journal.

3.1 In which countries is it most common to find research related to ML and flash floods?

Figure 5 presents 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 20 countries distributed throughout Asia, Europe, and North and South America. Most of the study areas are located in Asia (with a highlight on China (38%) and the Republic of Korea (8%)) and the United States (8%).

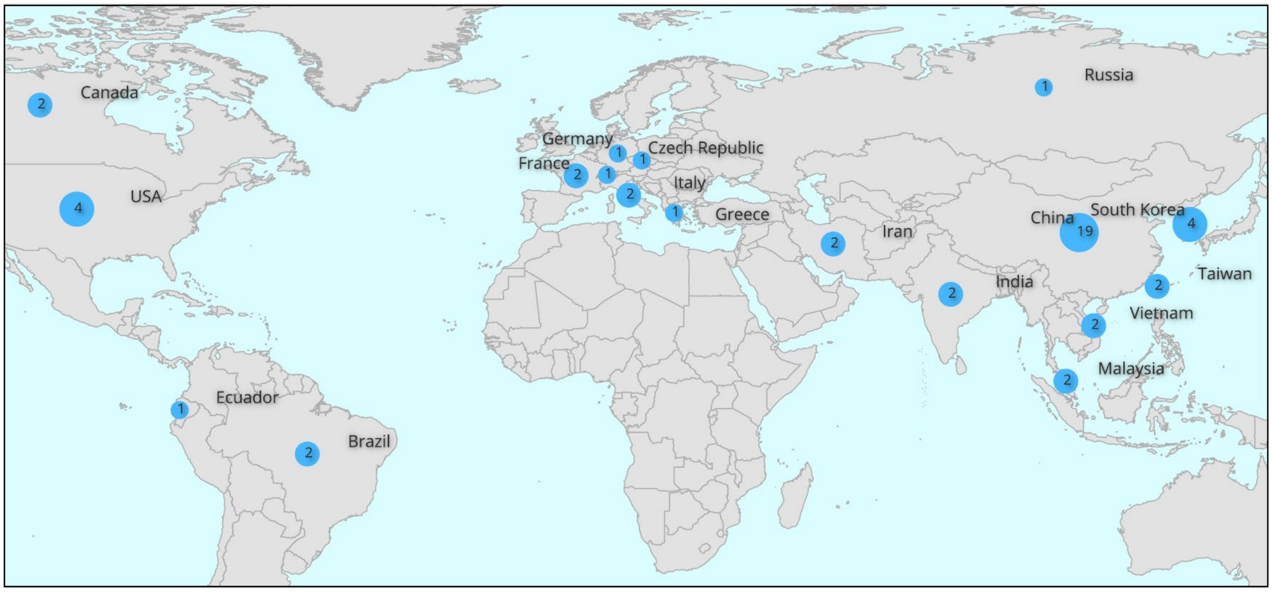

Figure 5. Frequency of articles applying machine learning (ML) to flash floods according to country application.

This scenario may be a reflection of 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 [30]. China is the country most severely threatened by flood disasters globally, with damages from such events between 1990 and 2017 accounting for approximately 10% of the world's total [31]. Flash floods, in particular, are widely recognized as a significant cause of human casualties and economic losses in China [32,33]. From the American perspective, flash floods result in the highest number of casualties among various flood events in the U.S. [34,35]. 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 [36]. Lastly, looking at the Republic of Korea, most small urban river basins in Korea have a very short concentration time, which leads to frequent and deadly accidents caused by flash floods during located heavy rainfall [37].

3.2 Which input and output data are most commonly used 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 used in 23 studies (46%), and water level data is employed in 19 studies (38%). 49 articles utilized as input data just one or an exclusive combination of the following measurements: discharge, rainfall, and water level. Only one work applied runoff solely as input data [38]. Notably, only four papers (8%) combined rainfall, water level, and discharge data simultaneously. Additionally, four studies used only rainfall data, three studies used only water level data, and two studies 4% used only discharge data. Figure 6 exposes the distribution of the input data used in the 50 studies analyzed in this work.

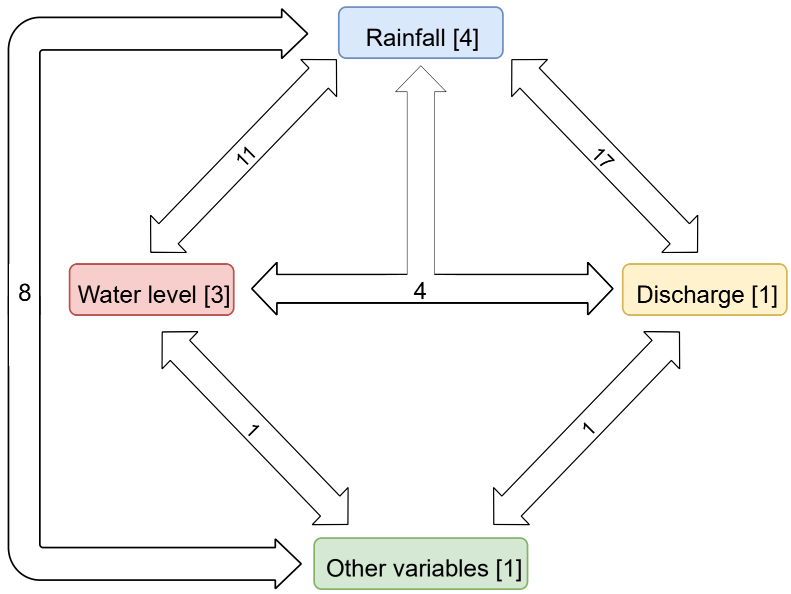

Figure 6. Distribution of the input data applied by the 50 analyzed articles. Values in [] mean the number of articles that used only this data as input; values within the arrows mean the number of papers that shares the input data.

It is worth noting that discharge and rainfall 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 [39].

Among the selected articles, 60% of the selected articles presented discharge as output, while 38% of them displayed water level as output. It is worth mentioning that only one article (2%) did not present either the discharge or water level as output. In [40], dynamic clustering and random forest techniques were used to identify flood types and select appropriate model parameters. Then, the Xinanjiang model for real-time flood forecasting was applied. In this approach, three flood indicators were identified as the most important factors characterizing flooding: flood duration, peak discharge, and runoff depth.

Lastly, although more than half of the articles provided discharge and water level as the output of their works instead of a flood extent map, most of them used historical flooding event records in their simulations, for example, to train a neural network or to endorse and/or validate their results, for example [41–46].

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 one of the methods in 60% of the works, followed by MLP, used in 28%. The revised studies also used CNN, tree-based methods (Decision Trees or Random Forests), and the Support Vector Machine (SVM), which were used, respectively, in 16%, 16%, and 14% of the papers. Other methods were employed, like k-Means, KNN, Extreme ML, Particle Swarm Optimization, and Fuzzy-based methods, on a minor frequency.

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

Method	Short Description	Papers in this review
AE [47]	Neural network architecture designed for unsupervised learning that learns to encode input data into a latent representation and reconstruct it with minimal loss	[48]
ANFIS [49]	Hybrid system that combines *fuzzy* logic and NN techniques for adaptive modeling and inference	[50]
ARMA [51]	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	[52]
BMA [53]	Statistical technique that combines Bayesian models in a temporal framework, considering changes in relationships between variables over time	[54]
CGBR [55]	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	[56,57]
CNN [58]	DL architectures adept at processing structured grid data, utilizing convolutional layers to learn hierarchical features automatically	[46,59–62]
Conv-LSTM [63]	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	[46,56,60]
DANN [64]	The Dynamic that adjusts the structure of the neural network during training	[65]
DNN [66]	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	[45]
DSTGNN [67]	Method for modeling dynamic spatiotemporal data, leveraging GNN to capture spatial dependencies and temporal dynamics efficiently	[68]
DT [69]	A ML algorithm that recursively partitions data based on feature values to create a predictive model represented by a tree-like structure	[70–73]
ELGBDT [74]	An ensemble learning technique that combines the strengths of Extreme Learning Machines and Gradient Boosted Decision Trees for efficient and accurate predictive modeling	[75]
Enconder-Decoder (ED) [47]	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	[62]
GAN [76]	DL 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	[38]

Table 2. Continuation.

GRU [77]	Type of RNN, designed to capture long-range dependencies in sequential data, featuring simplified memory cells and gating mechanisms for efficiency in training	[56,57,62,78,79]
k-Means [80]	Clustering algorithm that partitions data into K clusters based on similarity, iteratively adjusting cluster centroids until convergence	[40,71,73]
k-NN [81]	Lazy supervised learning method where a data point is classified by a majority vote of its k nearest neighbors	[52]
LSTM [82]	RNN designed to capture long-term dependencies in sequential data by utilizing specialized memory cells and gating mechanisms	[9,38,41,42,46,48,56,57,59–62,68,78,79,83–98]
MARS [99]	Statistical method for non-linear regression analysis, employing piecewise linear segments to model complex relationships between multiple predictor variables and a response variable	[71]
MLP [100]	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	[45,46,52,62,72,84,94,98,101–104]
OPENML [105]	Technique in ML that efficiently prunes irrelevant neurons from extreme learning machines to enhance model performance and reduce computational complexity	[71]
Random Forest (RF) [106]	An ensemble learning method in ML, consisting of multiple decision trees during training, resulting in improved accuracy and reduced overfitting through the aggregation of predictions.	[40,46,70,107]
RNN [108]	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	[45,95]
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	[57,61,62,84,102,110,111]
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	[98]
XGBoost [86]	Gradient boosting algorithm that efficiently handles various regression and classification tasks by sequentially adding weak learners, employing regularization techniques to prevent overfitting	[44,72]

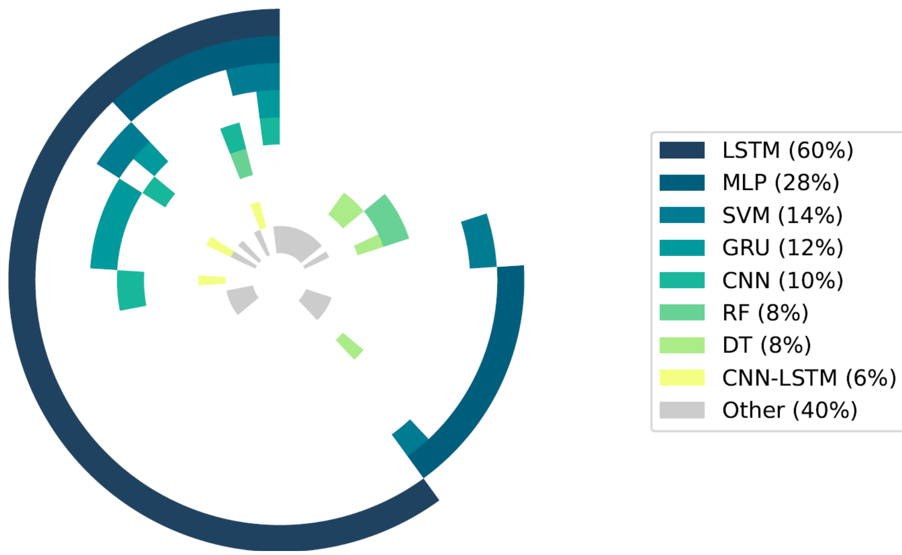

Figure 7. Frequency of machine learning (ML) methods for hydrological modeling of flash floods.

Figure 8 shows a comparison between all ML methods presented in the articles, including methods for comparing results and the main methods, which are 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. However, 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.

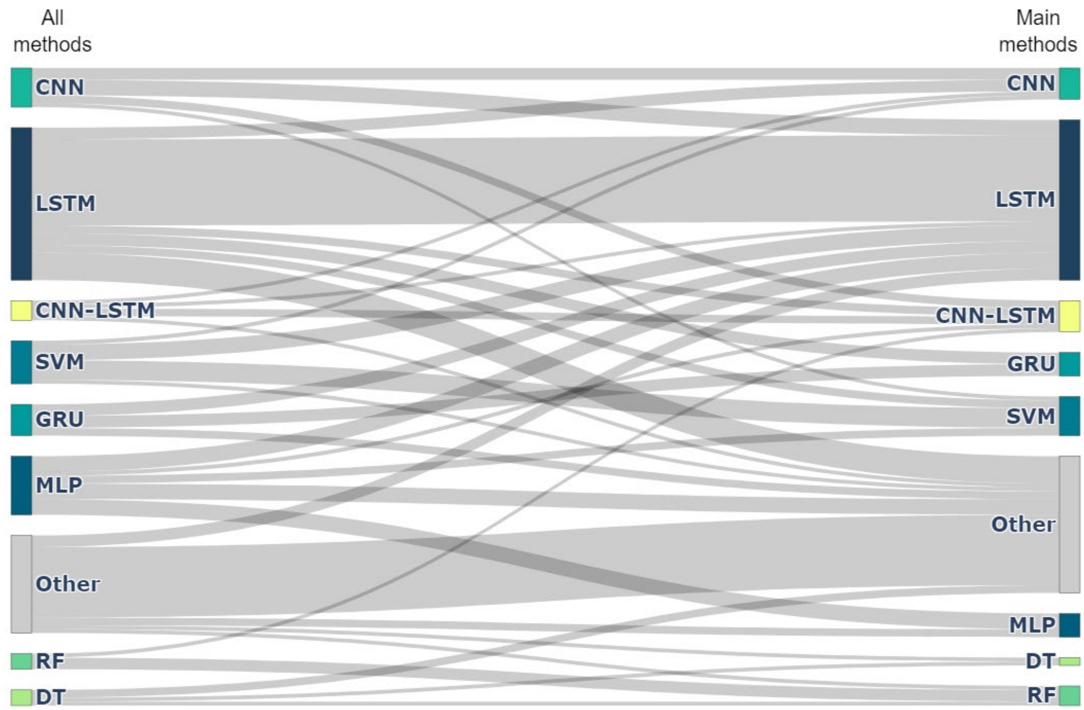

Figure 8. Proportion of all mentioned machine learning (ML) methods (left) and the main methods of each selected paper (right). A connection (gray line) from a method on the right to a method on the left means that those methods were compared in the same paper - and the method from the right in this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

3.4 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 [44] to 720 hours [48]. Most sub-hourly predictions employed multiple variables for training, typically a combination of water level and rainfall [44–46,83,88,90,101,104]. 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., [48]. The majority of the studies that applied LSTM methods foretasted discharge for lead times from 1 to at least 6 hours [9,41,42,46,48,60,84].

3.5 Is remote sensing widely used in ML hydrological models?

Despite being a common data source in many environmental studies and applications [73], remotely sensed data were observed in only seven works (14%) 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. Lastly, 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.

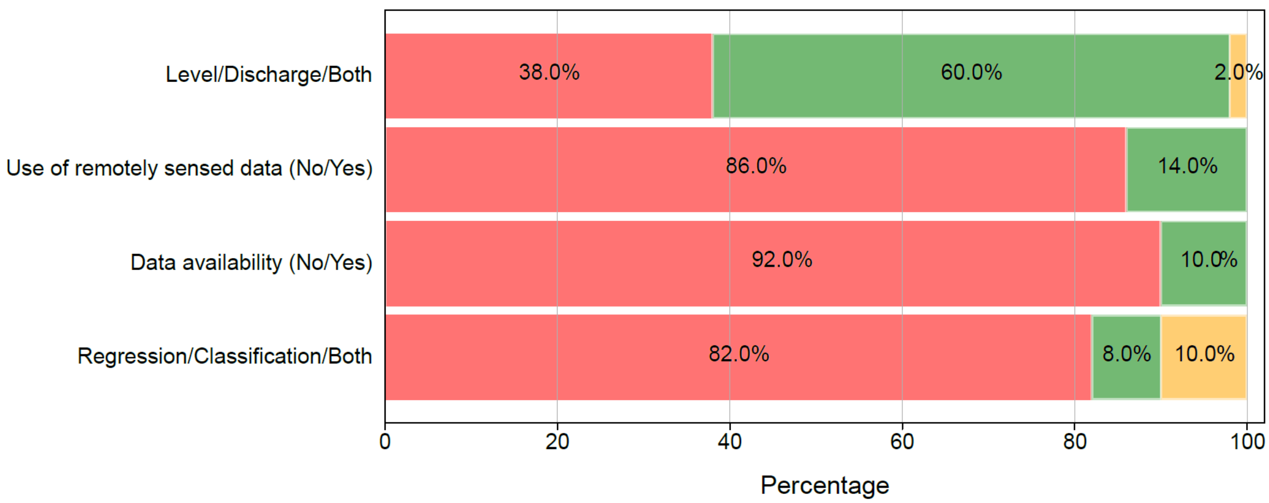

Figure 9. Ratio of the 50 articles that (i) presented water level, discharge, or both as output; (ii) used remotely sensed data; (iii) made data available; and (iv) applied regression, classification, or both.

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 [113].

3.6 Data availability

Among the reviewed articles, only 10% of them made the data used in the research publicly available [54,59,71,83,84], while 90% of them 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 most common method for predicting flash floods, according to the selected papers. As shown in Figure 9, 41 out of the 50 articles applied at least one regression algorithm to predict flash floods. Among them, four articles also applied a classification algorithm to tackle this problem. Furthermore, five articles used 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 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. Out of over 800 papers, 50 were selected that aligned with the scope of the SLR. Most of the studies examined focus on the regions of China, the US, and the Republic of Korea. Rainfall and discharge data emerge as the predominant input variables, and 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 data publicly 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 level 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.

The following presents 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 adopted data preprocessing step in ML. In addition to providing faster algorithms, it can also provide a better understanding of the underlying physical process being modeled [114]. Feature selection has been applied in a variety of studies of streamflow forecasting. In [115], a comparison of eight filter-based feature selection methods is performed for monthly streamflow forecasting. In [116], 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 [117]. Brand new research recognized the significance of this issue [118], 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 [119,120]. For example, [121] established a physics-informed ML (PIML) model to combine the predictive ability 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 including physical laws representing the spatial and temporal changes through computational methods for automatic differentiation [122]. 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 flash 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**
  Create standardized benchmarks based on diverse datasets and realistic scenarios and make 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 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 ML or AI by their authors, like [123,124]. Future versions of systematic reviews about flash flooding forecasting may consider explicitly statistical and physical based methods.

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Author contributions

Leonardo B. L. Santos: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Visualization, Writing—original draft, Writing—review & editing, Funding acquisition; **Luiz F. Satolo:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Ricardo S. Oyarzabal:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Elton V. Escobar-Silva:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Michael M. Diniz:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Rogério G. Negri:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Glauston R. T. Lima:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Stephan Stephany:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Jaqueline A. J. P. Soares:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Johan S. Duque:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Fernando L. Saraiva Filho:** Formal analysis, Investigation, Visualization, Writing—review & editing; **Luiz Bacelar:** Formal analysis, Investigation, Visualization, Writing—review & editing.

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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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