Flood Prediction using Hydrologic and ML-based Modeling: A Systematic Review

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***Abstract*—Flooding, caused by the overflow of water bodies beyond their natural boundaries, has severe environmental and socioeconomic consequences. To effectively predict and mitigate flood events, accurate and reliable flood modeling techniques are essential. This study provides a comprehensive review of the latest modeling techniques used in flood prediction, classifying them into two main categories: hydrologic models and machine learning models based on artificial intelligence. By objectively assessing the advantages and disadvantages of each model type, we aim to synthesize a systematic analysis of the various flood modeling approaches in the current literature. Additionally, we explore the potential of hybrid strategies that combine both modeling methods' best characteristics to develop more effective flood control measures. Our findings provide valuable insights for researchers and practitioners in the field of flood modeling, and our recommendations can contribute to the development of more efficient and accurate flood prediction systems.**

Keywords*—*Flood prediction; hydrologic model; machine learning; systematic review

I. INTRODUCTION

Floods are one of the most destructive and widespread natural disasters, inflicting severe environmental and socio-economic impacts worldwide [1]. In recent years, the frequency and intensity of floods have increased, underscoring the urgent need for accurate flood modeling to guide effective disaster response and management. Devastating floods have resulted in massive property damage, loss of human and animal lives, destruction of crops, and the propagation of waterborne diseases [2].

Understanding the intricacies of floods and accurately predicting their occurrence and severity is critical in developing strategies for flood management and mitigating potential damages. In the field of flood modeling, two primary approaches have been widely utilized: hydrologic models and data-driven prediction models. Hydrologic models aim to simulate the complex physical processes and interactions within the hydrological system, relying on high-quality data and hydrological expertise. However, these models face challenges in accurately evaluating uncertainty propagation and predicting real-time flood depths [3]. Conversely, data-driven prediction models, leveraging machine learning techniques, have shown superior accuracy and broad applicability in flood forecasting [3]. Nevertheless, a promising avenue for advancement lies in the hybridization of both approaches, harnessing the strengths of each to overcome the limitations.

The primary objective of this study is to explore and compare different modeling approaches employed in flood modeling, specifically categorizing them into hydrologic models and data-driven machine-learning-based models. The research aims to address the existing knowledge gaps in flood modeling and shed light on the diverse methodologies used in simulating and understanding flood events.

To achieve this objective, the study presents an analysis of the strengths and limitations of both model types. Furthermore, it highlights the potential benefits of integrating these approaches to create more robust and accurate hybrid models. The study analyzes a comprehensive range of sources, including case studies, real-world data, and academic research, to provide a well-rounded evaluation of flood modeling techniques. The article introduces and compares one-dimensional (1D), two-dimensional (2D), and three-dimensional (3D) hydrologic models, with a focus on their capabilities, limitations, and applications in flood hazard simulation and prediction. Additionally, the study delves into the advantages of hybrid models, demonstrating how their integration can contribute to more effective flood management strategies.

Contribution: This article's main contribution is to provide valuable insight into flood modeling, and advancement in the field, and ultimately aid in better understanding and managing flood events. By combining a thorough exploration of modeling approaches with a critical assessment of their performances, this study aims to lay the foundation for more resilient flood management practices in the face of escalating climate challenges. The article is structured as follows:

Section II provides the systematic approach adopted to gather related work and literature review along with bibliometric analysis. Sections III and IV provide introductions to various subdomains in Hydrologic modeling and Machine-learning-based modeling, respectively. Sections V and VI analyze the literature review on Hydrologic modeling and Machine-learning-based modeling, respectively. Section VII provides the analysis and discussion, while Section VIII provides the conclusions.

II. Bibliometric Analysis of Hydrologic Modeling and Machine Learning in Predicting Flood

The study focused on examining the trends and patterns in research publications in the field of flood prediction using machine learning-based modeling and hydrologic modeling. Two widely used databases, Web of Science (WoS) and Scopus, were utilized to gather relevant research papers. Additionally, the Dimension database was included to ensure comprehensive coverage of the literature. To visualize and analyze the data, VOSviewer software [4] was employed, along with traditional methods of data representation.

Using information from the Scopus and WoS databases, the bibliometric analysis produced the two instructive visualizations shown in Fig. 1 and Fig. 2. The size of the circles in Fig. 1 represents the number of citations each document in the hydrologic modeling and flood prediction domain has received. Greater circles indicate more citations, which reflects the importance and influence of the corresponding works on this topic. Similar to Fig. 1, but with a focus on machine learning modeling, Fig. 2 shows the citation distribution for the same domain.

Similarly, Fig. 2 and Fig. 3 show the number of citations in the context of machine learning and Hydrologic Modeling in flood prediction. Bibliometric analysis software VOSviewer was used to create both visualizations. A better knowledge of the current trends and contributions in hydrologic modeling and machine learning applied to flood prediction research is made possible by these numbers, which provide insightful information about the research environment by highlighting the most important and cited articles in both fields.

Table I lists how many articles have been written about using hydrologic modeling and machine learning techniques to anticipate flooding. The article counts or publication records for each type of study are shown in the table, indicating the volume of research done in the field of hydrologic modeling and machine learning for flood prediction across the various databases.

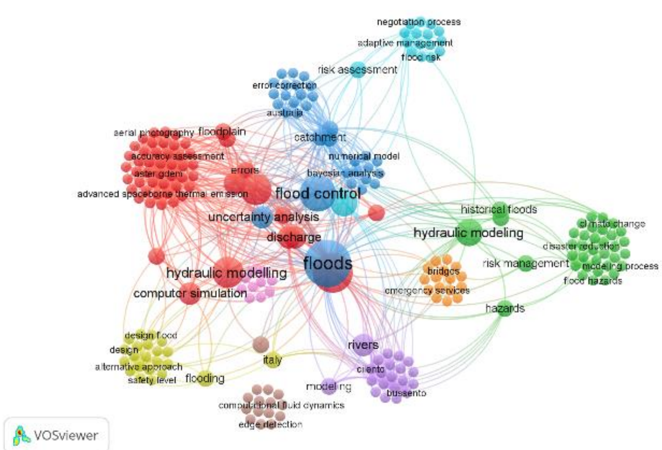

Fig. 1. Map the hydrologic modeling and "Flood prediction" network – Scopus.

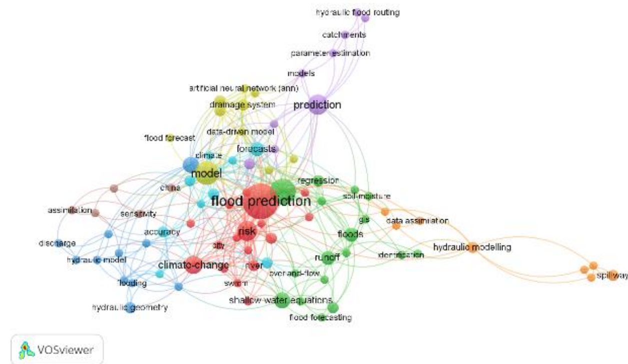

Fig. 2. Map the hydrologic modeling and "Flood prediction" network- WoS.

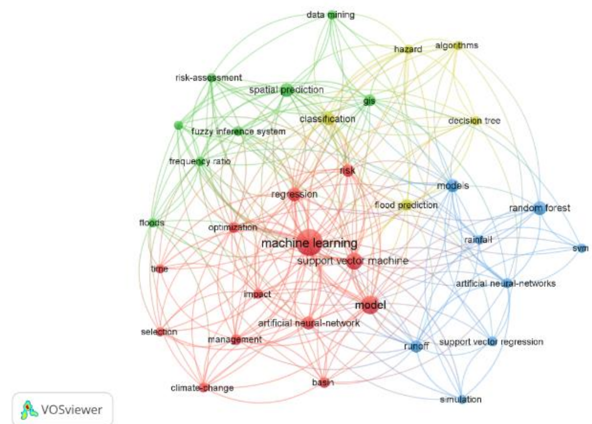

Fig. 3. Map machine learning and "Flood prediction" network WoS.

TABLE I. The Number of Articles Related to the Use of Hydrologic and Machine Learning in Flooding Prediction

Topic \ Database	***WoS***	***Scopus***	***Dimension***
Hydrologic	1493	1249	1255
Machine learning	3,027	2280	3,730

A. Bibliometric Analysis

The bibliometric analysis revealed an interesting trend in the distribution of research papers. It became evident that there is a significantly higher number of research papers dedicated to machine learning compared to those published in the field of hydrologic modeling (see Fig. 4, 5, 6, and 7). This indicates a greater emphasis on the utilization of machine learning techniques in flood forecasting research.

The higher number of research papers on machine learning suggests that it has gained significant attention and interest in the field of flood forecasting. Machine learning techniques offer the potential to improve the accuracy and efficiency of flood prediction models by leveraging large datasets and complex algorithms. On the other hand, the relatively lower number of research papers on hydrologic modeling may indicate a need for further exploration and development in this area. The findings of this study provide valuable insights for researchers and practitioners interested in the field of hydrologic modeling, machine learning, and flood forecasting.

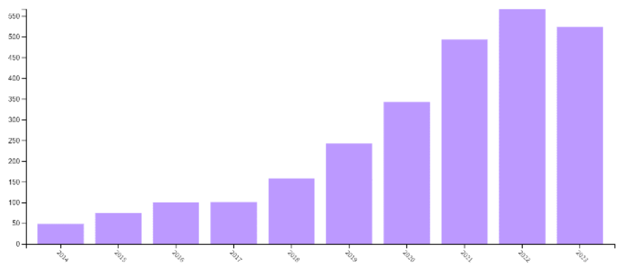

Fig. 4. Publications over time: Machine Learning and "Flood Prediction" WoS.

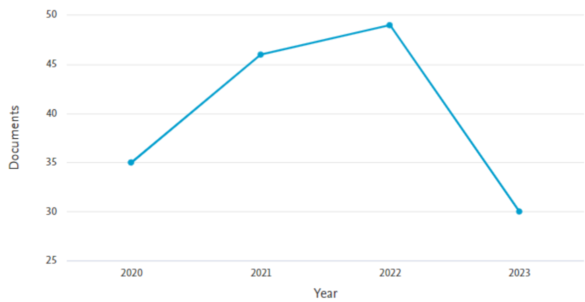

Fig. 5. Publications over time: Machine Learning and "Flood Prediction" Scopus.

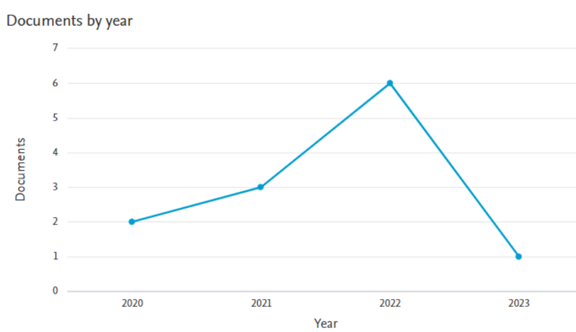

Fig. 6. Publications over time: Hydrologic Modeling and "Flood Prediction" Scopus.

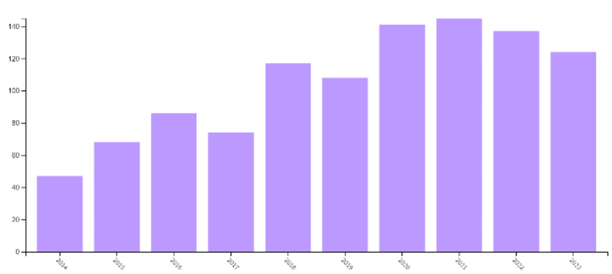

Fig. 7. Publications over time: Hydrologic modeling and "Flood prediction" WoS.

III. HYDROLOGIC MODELING

Hydrologic modeling plays a crucial role in simulating and predicting flood hazards, enabling a deeper understanding of the complex dynamics associated with floods. This modeling approach encompasses various techniques, including one-dimensional (1D), two-dimensional (2D), and three-dimensional (3D) models, each offering unique advantages and limitations. This study delves into these different modeling approaches, exploring their applications, capabilities, and challenges in simulating flood events. By examining the strengths and limitations of each modeling method, the study aims to enhance the understanding of hydrologic modeling and its significance in effectively managing and mitigating the impacts of floods.

Fig. 8 shows the hydrologic model configured for 1D, 2D, and coupled 1D/2D simulations (a, b, and c) [5]. The 1D simulation in panel (a) shows a condensed version of the hydrologic system that works well in settings with linear flow patterns. The 2D simulation, which considers two-dimensional flow characteristics, illustrates the hydrologic processes in more detail in Panel (b). The coupled 1D/2D simulation, which combines both methods in panel (c), enables a more precise and in-depth portrayal of complicated flow interactions in situations when both 1D and 2D models are required. This figure helps academics and practitioners choose the best strategy based on particular modeling requirements and objectives by providing a useful visual reference for understanding the various modeling setups and their applications in hydrologic simulations [5].

A. One-Dimension Hydrologic Modeling

Various authors have discussed the effectiveness of hydrologic modeling methods in simulating and predicting flood hazards. For example, a study conducted by Ambiental Environ-mental Assessment [6] demonstrates that the 1D model effectively captures the interconnected network of a river by linking multiple cross-sections that traverse both the land and the river. Through this model, the water level is simulated and allowed to flow in a single direction along the channel. Additionally, the model accommodates the possibility of reverse water flow, such as in cases where the presence of structures obstructs the passage of water. Pinos et al. [7] highlight that river flood events are among the most frequent and economically burdensome natural disasters. Despite floods being a natural component of the hydrological cycle, they have far-reaching environmental consequences and can cause significant human and financial losses. Consequently, the utilization of modeling techniques becomes essential in simulating and predicting these occurrences.

Pinos et al. [7] conducted a study on the performance of the hydrologic 1D model approach in approximating flood levels for a mountain river. The study utilized HEC-RAS, Mike 11, and Floor Modeler as modeling tools. In the case of HEC-RAS, high-resolution cross-section surveys were conducted at intervals of 25 meters along the river line. The validation of the model was based on historical flood regions with return periods ranging from 2 to 10 years. The findings of research [7] served as reference models for different return periods and were compared to other models. The 1D model is considered an acceptable approximation as long as the water remains within the roadway profile. However, when the flow in the streets exceeds the curbs, there is a potential for the flow direction to shift, making the 2D model more suitable at that point [8]. It is important to note that using the 1D hydrologic modeling approach has certain limitations. One major limitation is the assumption that the floodplain between the various cross-sections of the river is similar. Additionally, there is a need to determine the specific number and spacing of cross-sections to accurately represent the river channel and neighboring topography, and the guidelines for establishing these parameters are limited [10].

B. Two-dimensional Hydrologic Modeling

2D flood modeling is an approach used to analyze and interpret the two-dimensional flow of water during anticipated flood events. It relies on digital terrain modeling and the bathymetry of water channels to establish the depth of water and depth-averaged velocity on a mesh or grid [11]. One of the advantages of this modeling technique is that it does not require predefined flow routes, allowing for a more flexible representation of the flow dynamics.

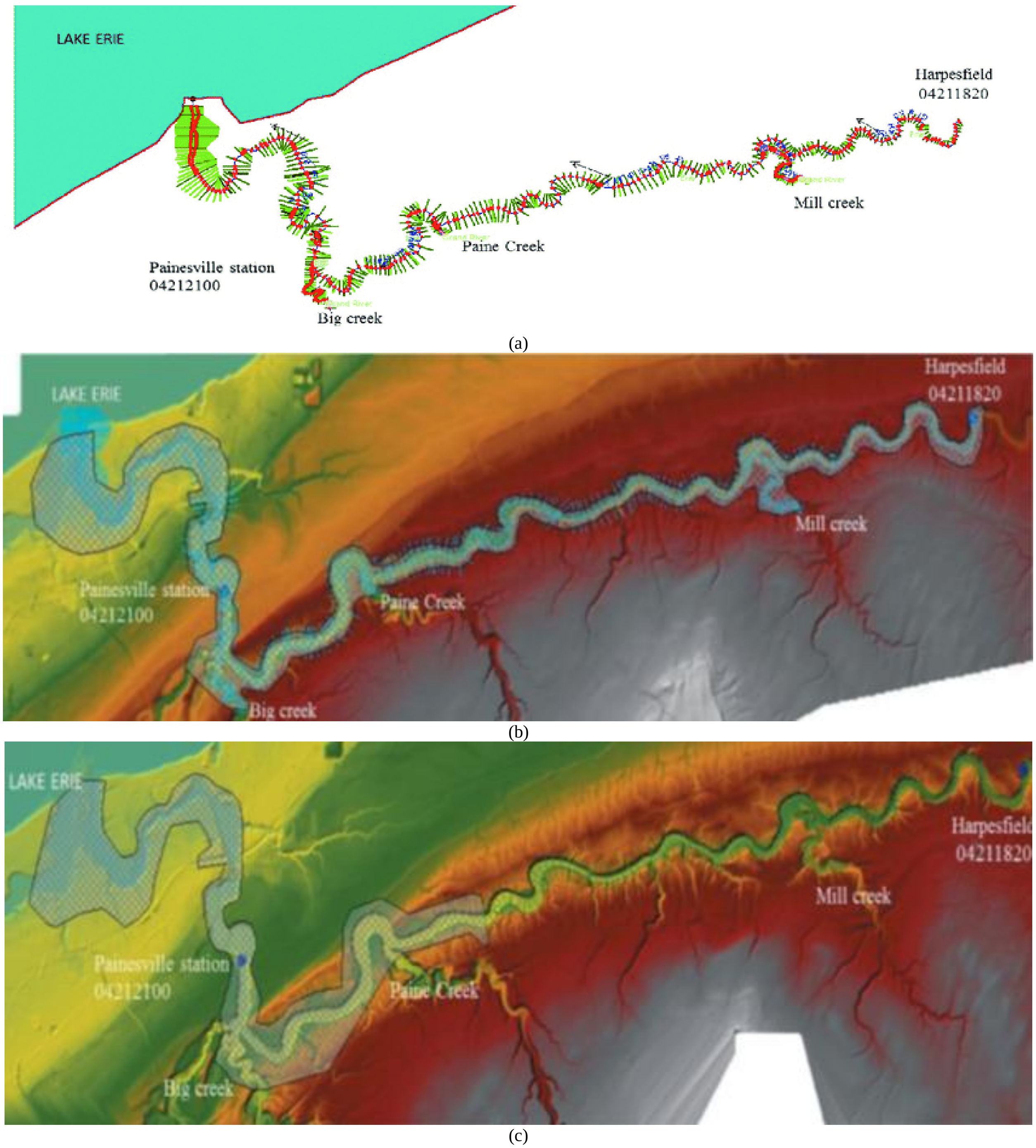

Fig. 8. Hydrologic model set up of (a) 1-D simulation, (b) 2-D simulation, and (c) coupled 1-D/2-D simulation [5].

An example of the application of 2D flood modeling can be seen in the assessment of the Medjerda River conducted by Gharbi et al. [12]. The researchers utilized 2D hydrologic modeling to understand the behavior of the river and accurately estimate the extent of flood zones. Their findings demonstrated that 2D analysis provides a more precise depiction of the flooded region compared to the one-dimensional (1D) unsteady flow study. The visual representation of flood extent through 2D model maps is superior to the traditional water-depth curves used in 1D models [9].

However, it is important to acknowledge the limitations of the 2D modeling approach. Firstly, the complexity of the 2D model makes it more computationally costly compared to 1D models. The computational time required for a complete run of a 2D model is significantly longer, often taking hours as opposed to minutes for a 1D model [8]. This can pose challenges for inexperienced hydrologists who may struggle with the complexity of the model and the efficient transfer of information to relevant departments.

Furthermore, the application of 2D modeling may be hindered by the availability of quality data. High-quality data, obtained through on-site sensors and Internet of Things (IoT) devices, is crucial for achieving accurate results [12]. Additionally, when analyzing flood risk within large cities and complex structures, relying solely on 2D geographical data may not be effective. In such cases, the integration of 3D city model-based GIS solutions becomes necessary to provide decision-makers with comprehensive information [13].

C. *Three-dimensional Hydrologic Modeling*

3D modeling involves the mathematical representation of surfaces in three dimensions, utilizing specialized software to manipulate vertices, edges, and polygons in a simulated 3D space [14]. When it comes to simulating and predicting flood hazards, 3D models have proven to be computationally expensive but crucial for accurately representing the three-dimensional flow around urban areas and interactions between flood waves and constructed buildings [15].

In the context of flood simulation and its impact on utilities, Adda et al. [16] emphasize that 3D modeling offers robust visual depictions that enable decision-makers to assess the safety of buildings located in flood zones. Their research explores the use of LiDAR (Light Detection and Ranging) data and 3D modeling to analyze flood risk on government utilities and buildings. LiDAR data is highlighted as an inexpensive and comprehensive method for multidimensional 3D mapping [16].

Data collection for 3D modeling often involves ground-controlled points obtained through GPS methods. Adda et al. found that their 3D approach revealed regions that were potentially situated on low-lying terrain prone to flooding. This information is vital for emergency decision-making and prioritization. The use of 3D hydrologic modeling enables rapid reaction, alert, and warning systems, mitigation strategies, and effective planning and management of complex geographic issues.

By utilizing 3D geospatial data, planning challenges can be better addressed, and conditions that may increase the risk of flooding can be identified. This aids in understanding and evaluating the nature of dangers and facilitates the development of clear management strategies for rescue operations. Additionally, one significant advantage of 3D hydrologic modeling is the ability to test infrastructure projects before implementing them on the ground, minimizing potential risks [17].

However, it is important to acknowledge the limitations of the 3D modeling approach. While it offers valuable insights, it is more suitable for localized hydrologic issues and may require substantial details, resulting in longer simulation times [17], [18].

D. *Discussions*

The evaluation and discussion of 1D, 2D, and 3D modeling methodologies for flood simulation and prediction emphasize the advantages and disadvantages of each methodology as well as some of the field's practical uses.

A common technique for simulating flow in a single direction along a channel is 1D hydrologic modeling. As long as the water stays inside the roadway profile, it offers a simplified portrayal of flood threats and is supposed to be acceptable. The primary benefit of 1D modeling is that it is straightforward and computationally efficient, making it appropriate for use in large-scale applications. A drawback of this method is that it necessitates particular rules for setting cross-section spacing and assumes uniform floodplain features between cross-sections.

On the other hand, 2D hydrologic modeling, which considers the two-dimensional flow of water and incorporates digital terrain modeling and bathymetry, provides a more in-depth simulation of flood events. It enables the depiction of flood inundation patterns and offers a more precise estimation of flood extent. The use of 2D models is particularly valuable when the flow exceeds the curbs and shifts direction, such as in urban areas with complex topography and structures. However, 2D modeling is computationally more expensive and requires high-quality data, including LiDAR data, to achieve accurate results [19].

It may also pose challenges for inexperienced users and information transfer to relevant departments. Additionally, it might make it difficult for new users to transmit information to the appropriate departments.

The study also emphasizes the value of 3D modeling in assessing flood risks, particularly when it comes to examining three-dimensional flow patterns around built-up areas and their interactions. 3D models enable precise simulation of flood impacts on utilities and infrastructure and offer a more thorough understanding of flood wave behavior. They give decision-makers useful information that enables them to evaluate the security of structures in flood-prone locations and prioritize emergency responses. By offering visualization tools, assessing hazards, and testing infrastructure projects before execution, 3D modeling also helps with planning and management. 3D modeling, on the other hand, necessitates specialist tools and comprehensive data and is more difficult and computationally expensive. It may take longer to simulate problems and is best suited for limited hydrologic problems.

IV. Machine Learning Algorithms in Flood Prediction

The destructive nature of floods has necessitated the advancement of flood prediction as a basis for risk reduction, policy suggestions, and minimizing property damage and loss of life. These requirements have led to the development of machine learning algorithms that mimic the mathematical expressions utilized in examining the physical processes of floods over the past two decades. In their study, Mosavi et al. [20] acknowledged that machine learning methods have improved prediction accuracy and provided cost-effective solutions, which has contributed to their increased popularity among hydrologists. Fig. 9 shows the fundamental steps in creating an ML-based model.

A systematic review revealed that several critical factors guide the selection of machine learning methods, including robustness, speed, computation cost, and generalization capability. Lawal et al. [21] discovered that the popularity of machine learning in predicting flood alerts and reducing the impact of floods arises from its low computational requirements, as it relies on observational data. However, a comparative study conducted by Lawal et al. [21], which evaluated logistic regression, support vector classification, and decision tree algorithms, highlighted the importance of considering performance accuracy, recall, and receiver operating characteristics when choosing machine learning algorithms for flood prediction.

Machine learning has made it possible to monitor the changing patterns of river water levels, which helps mitigate the socioeconomic implications caused by floods. According to Mosavi et al. [20], popular machine-learning methods for flood prediction include ANNs, SVM, SVR, ANFIS, WNN, and DTs. However, hybridization through various methods is also common. The study also found that the data decomposition technique is preferred to improve dataset quality and prediction accuracy, while ensemble methods facilitate generalization and reduce prediction uncertainty.

In addition, Mosavi et al. [20] identified that applying add-on optimizer algorithms improves prediction quality by tuning ANNs to optimal neuronal architectures. In a study on the detection of flooding from river water levels, Zehra [22] observed that non-linear (NARX) and support vector machines (SVM) are viable machine learning methods. The study revealed that NARX and SVM utilize hydrological resource variables such as precipitation amount, seasonal flow, peak gust, and river inflow, which are regressed into flood and non-flood classes.

Accurate prediction of floods and other hydrological events is crucial for water resource management techniques, policy development, and evacuation models. Improving prediction systems for short- and long-term flood events is significant in minimizing damage. It is important to note that machine learning (ML) approaches for flood prediction can vary significantly depending on the specific application, dataset, and type of prediction required.

For instance, ML approaches for predicting short-term water levels may differ greatly from those used for predicting long-term stream flows. When building an ML model, all the available data undergoes training, validation, verification, and testing processes [23]. These steps ensure that the model is trained effectively and performs accurately when applied to new data.

Overall, the development and utilization of ML models in flood prediction play a crucial role in improving the accuracy and effectiveness of water resource management, policy ideas, and analyses, as well as evacuation planning.

When accurate data are available, machine learning approaches can be a powerful tool in risk analysis. However, the findings obtained from these approaches may not be as sophisticated or predictable as those from model-driven studies, such as hydrodynamic models [24]. The use of a data-driven approach with machine learning for predictive studies can be relatively straightforward, particularly in the presence of uncertainty related to climate change.

One of the key advantages of using machine learning prediction models is their ability to capture flood nonlinearity based solely on historical data, without requiring an understanding of the underlying physical processes. Data-driven prediction models based on machine learning hold promise as they are easier to construct and require fewer inputs. Over the past two decades, the continuous improvement of machine learning algorithms has demonstrated their usefulness in flood forecasting, often surpassing conventional approaches in terms of performance and accuracy [25]. The distinguishing factor of machine learning technology in flood prediction is its ability to extract crucial information solely from input data without the need for specialized knowledge [26].

It is important to consider certain aspects of machine learning algorithms. Firstly, their performance is only as good as the quality of their training, which involves the system learning the intended task from previous data. Therefore, ensuring robust data enrichment is crucial in machine learning algorithms. Secondly, the competence of a machine learning algorithm varies depending on the specific task, which is commonly known as the "generalization problem." It refers to how effectively a trained system can forecast situations for which it was not specifically trained [20].

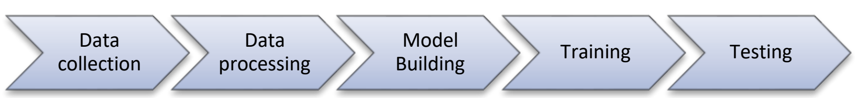

Fig. 9. The fundamental steps for creating a machine learning (ML) model.

Wagenaar et al. [27] discovered that the field of flood risk analysis, focusing primarily on rare extreme events, often faces challenges in data collection during such events, resulting in a lack of data for machine learning applications in flood risk and impact modeling, particularly for effective model training. However, advancements have been made in utilizing machine learning for descriptive hazard assessment using data from social media. Machine learning algorithms are effective optimization approaches rather than black box models, offering efficiency, reliability, and quick convergence at low computational costs.

The following are some commonly used ML algorithms in flood prediction:

A. ANNs: Artificial Neural Networks

The most often used algorithms for modeling flood prediction are ANNs. ANNs interpret historical data rather than the physical qualities of a catchment. As a result, ANNs are regarded as trustworthy data-driven tools for building sophisticated and nonlinear black-box models of the links between rainfall and flood. Despite their benefits, ANNs have several disadvantages, including network architecture, data management, and the inability to physically perceive the modeled system. The comparatively low precision while employing ANN is a significant disadvantage [20].

B. MLP: Multilayer Perceptron

The MLP is a class of FFNN that trains its network of interconnected nodes with multiple layers using supervised learning from BP. The MLP is characterized by simplicity, nonlinear activation, and a large number of layers. These qualities led to the model's widespread application in complicated hydrogeological models and flood prediction. MLP models were shown to be more effective and more generalizable in a review of ANN classes used in flood simulation. However, it is typically discovered that the MLP is more challenging to optimize [28].

C. SVM: Support Vector Machine

SVM, a supervised learning machine that operates on the statistical learning theory and the structural risk minimization (SRM) rule, is very well-liked in flood modeling. To reduce the predicted error and overfitting concerns of a learning machine, the SRM principle operates as a tradeoff between the quality and multidimensional character of the approximation function [29]. The SVM's training method creates new, non-probabilistic binary linear classifiers that maximize the geometric margin through inverse problem-solving and minimize the empirical classification error. Hydrologists use SVM extensively for flood prediction [20]. SVM, which is based on the structural risk reduction concept, is a reliable and efficient method for equation fitting, data analysis, hydrological forecasting, and other applications. Furthermore, SVM is used to handle small sample, non-linear, and high-dimensional pattern recognition problems and has unique benefits. SVM may be applied to classification as well as regression issues [30].

SVM applications are widely used in hydrological modeling and flood predictions. SVM's enhanced form as a regression tool supports vector regression (SVR) is a developed and efficient alternative procedure for dealing with regression difficulties during the last two decades by giving alternative loss functions. SVR is based on mapping and solving the original data into a high-dimensional feature space using linear and/or nonlinear regression classification. SVR formulation is based on SRM rather than ERM, which minimizes an upper bound of the generalization error rather than the prediction error on the training set [29].

SVM and other data-driven ML models rely on the quality and amount of training data as well as model optimization parameters. If the data is insufficient and inadequate to cover the differences, their learning falls short and, as a result, they cannot achieve reasonable accuracy. The disadvantages of SVM-type ML models for dealing with the "generalization problem" might be mitigated by a strong and complete understanding of ML techniques, as well as user-specified practical solutions [29].

SVM is essentially a linear machine and can be thought of as a statistical tool that solves issues using an approach akin to Artificial Neural Networks (ANN). Its approximate use of the Structural Risk Minimization (SRM) concept aids in its ability to generalize effectively to new data. While it has all the advantages of ANN, it also addresses some of the fundamental flaws that were observed in the ANN application. [31]. ANNs employ empirical risk minimization, but SVMs use structural risk minimization to handle the overfitting problem by balancing the model's complexity against its success in fitting the training data. [35].

The reason why the SVM algorithm is more popular in flood prediction than other algorithms is SVM may automatically choose the critical vectors in the training process as support vectors and delete the nonsupport vectors from the model. As a result, the model performs effectively in noisy environments. Furthermore, with certain crucial real training vectors encoded in the models as support vectors, SVM can trace back historical occurrences to enhance future forecasts with lessons learned from the past. Because the input vectors of SVM are fairly versatile, it is quite simple to integrate other relevant elements into the model (such as temperature, evaporation, date, etc.). Because SVM parameter optimization is a convex issue, there is only one optimal point, unlike ANN which has more than one optimal [33].

D. DT: Decision Tree

Because DTs are rapid algorithms, ensemble models to simulate and predict floods have become increasingly popular. The classification and regression tree (CART) is a common DT type used in machine learning. The decision tree is very useful for determining the level of risk of flooding [34].

E. GA: Genetic Algorithm

A genetic algorithm had been created by Holland. The survival of the fittest is the foundation of the idea. It uses chromosomes, which have several genes on each one. Every gene represents a choice variable (or model parameter), and every chromosome represents a potential best-case scenario [35].

F. ACO: Ant Colony Optimization

Dorigo developed the ACO after becoming curious about how ants choose the quickest route between their colony and a food source. It was discovered that although ants cannot see, they can communicate with one another via a chemical called a pheromone. Each spreads a scent along its course. Ants are therefore likely to select the route with the highest concentration of pheromone. According to this, ants will finally take the shortest way if there are both lengthy and short routes leading from the nest to the food source [35].

V. Analysis of Hydrologic Modeling Techniques

When it comes to hydrologic modeling, deciding between a steady-state and a non-steady-state flow is significantly easier. Although 2D modeling can yield better results in some cases, there are also scenarios where 1D modeling can produce outcomes equally as good as or better than 2D models, with less work and computing resources. Many situations are complex, and it is possible to include both the positive and bad aspects of each approach depending on the context.

A few instances of scenarios in which it is believed that 2D modeling is preferable to 1D modeling are as follows:

Water may flow in several directions if a levee is broken or overtopped in a model region located behind a levee system. Before it reaches the lowest point and begins to pool and maybe overtop or breach the levee on its lower end, water can flow overland in the protected region in several different ways thanks to the slopes present there. When the protected area is relatively small, and the entire area eventually fills to the level of a pool, a 1D model may accurately predict the ultimate water surface and the extent to which the region will be inundated.

Tides, river flows, and other water sources entering an estuary or bay can cause the water to flow in various directions—a place or occurrence where the water's flow path is not entirely clear. It is challenging to forecast flood occurrences due to the episodic character of flow evolutions on alluvial fans. This is because the channels' whole direction may shift while the event takes place, making it impossible to generate accurate predictions.

It is best to avoid making sharp bends when there is a good chance that considerable super elevation may occur. Because flood plains are expansive and level, the water that leaves the overbank zone may go in various directions. Measurements of precise velocities are required to correctly analyze the hydrology of flow around an item.

Because of the complexity of urban terrain, flows on the urban surface are often substantially different from flows in channels. In recent years, several examples have been explored and applied to coupled 1D/2D techniques, in which the urban surface is represented using two-dimensional (2D) flow approaches and combined with a 1D pipe network model. Roads, buildings, barriers, and other elements of metropolitan surfaces abound [30]. These structures, particularly buildings, will alter the direction and velocity of the flood water, resulting in a variety of complicated flow pathways. The information on the buildings may be distorted or lost if the grid resolution is too coarse. Models with finer grid resolutions may offer more precision and a more accurate depiction of physical processes.

Constructing an entirely 3D model is more complex, but once it has been constructed, changes to the design may be made methodically and straightforwardly. Applying design changes in a 2D model is more challenging than in 3D.

There are three types of instruments for predicting hydrological variables: conceptual, physically based, and "black-box" models. The underlying physics of the first two categories, which may be represented by either simplified relations or partial differential equations in one or two dimensions, must be understood. Furthermore, using these models to forecast rainfall/runoff processes and/or river routing also calls for a significant amount of topographic, land-use, and other information that might not be accessible. Additionally, the lengthy calculation requirements associated with this method, particularly when two-dimensional models are required, sometimes limit real-time forecasting derived from physically based models [36].

VI. Analysis of Machine Learning Techniques for Flood Prediction

This study on hydrologic modeling and machine learning in flood hazard assessment gives a thorough examination of machine learning techniques for flood prediction in this section. This analysis's goal is to assess the usefulness and applicability of several machine-learning strategies for anticipating flood dangers.

A. Evaluation Standards for Prediction

Establishing evaluation standards that cover accuracy, dependability, robustness, consistency, generalization, and timeliness is essential for creating accurate flood prediction models. These standards act as the basic rules for evaluating the efficacy of flood prediction models and guaranteeing their dependability in practical implementations.

B. Metrics for Performance Evaluation

Root-mean-square error (RMSE), mean error (ME), mean squared error (MSE), Nash coefficients (E), and correlation coefficient (CC or R^2) are some of the performance evaluation metrics for flood prediction models that are frequently utilized. These measures allow for a quantitative evaluation of the model's prediction skills and make it easier to compare various strategies.

C. Analysis of Various ML Algorithms in Flood Prediction

The study identifies the advantages of ANNs, such as enabling working with huge datasets, and the benefits and drawbacks of particular ANNs, such as Backpropagation Neural Networks (BPNN), functional networks, and the NARX network. The study also investigates how the inclusion of autoregressive models can improve the precision of flood forecasts.

The performance of the MLP and various DT models, such as the ADT model, the Rotation Forest (RF), and the M5 model tree (MT), is specifically examined. The study draws attention to their strength and effectiveness, particularly in cases with lengthy lead times.

SVM's excellent generalization capacity, promising hourly flood prediction results, and uncertainty evaluation for potentially dangerous flood quantiles are identified.

D. Hybrid Designs

The study investigates the effectiveness of hybrid models like the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Wavelet Neural Network (WNN) for longer-term flood predictions that last longer than two hours. ANFIS's excellent capacity to predict flash floods in real-time, as well as its high accuracy and dependability is also identified. The study also looks at the advantages of sophisticated ANFIS hybrid models calibrated by Support Vector Regression (SVR) for nonlinear and real-time flood prediction, highlighting their enhanced prediction accuracy and cost-effectiveness.

E. Ensemble Methods

Finally, the study looks into cutting-edge hybrid models and ensemble techniques that combine statistical, soft computing, and machine learning techniques to improve flood prediction models. It examines Ensemble Prediction System (EPS) techniques, such as ANN, MLP, SVM, and RF ensembles, which show promise in enhancing prediction precision, and robustness, and lowering model uncertainty.

Table II lists the machine-learning techniques that have been applied to flood modeling. Although data-driven technologies, artificial neural networks (ANNs) have limits when it comes to understanding systems. The Multilayer Perceptron (MLP) is straightforward but difficult to optimize. Small sample sizes are effectively handled by a Support Vector Machine (SVM), but it requires high-quality data. Although Decision Tree (DT) is rapid and appropriate for flood modeling, more study is required. The Genetic Algorithm (GA) seeks the best options, but it depends on accurate encoding. For hydrogeological modeling and flood prediction, these methods have advantages and factors to consider.

An accurate forecast should be judged by its accuracy, dependability; robustness; consistency; generalization; and timeliness [37]. Durable and simple models are the best way to ensure that projects are completed on schedule. Using various root-mean-square errors (RMSE) can also evaluate the accuracy of forecasting models, mean error (ME), mean squared error (MES), and R^2 correlation coefficients, as well as the mean and squared errors for each model tested (CC). *RMSE* and R^2 values close to one indicate that flood forecasting models are generally reliable (Calculated using Eq. (1) and Eq. (2) respectively).

The flood forecasting models' reliability can be determined by examining their *RMSE* and R^2 values, where values close to one indicate higher reliability (calculated using Eq. (1) and Eq. (2) respectively). By referencing [20] and reviewing approximately 45 references, the study extracted and presented the results in Fig. 10 and Fig. 11. Evaluations of this study considered various factors, including the dataset, processing cost, and specific application. The study also assessed the method's generalizability, speed, installation cost, ease of use, and maintenance expenses. Standard deviation (RMSE) was measured using a single unit for accurate representation, and thorough confirmation ensured the absence of errors. R^2 and *RMSE* were utilized to assess the performance of single and hybrid ML approaches for short-term flood forecasting, as depicted in Fig. 10 and Fig. 11, based on Mousavi's research [20].

$$R^2 = \frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{(\sum_{i=1}^{N}(x_i-\bar{x})^2)*(\sum_{i=1}^{N}(y_i-\bar{y})^2)}} \tag{1}$$

$$RMSE = \sqrt{\frac{(\sum_{i=1}^{N}(x_{obs,i}-x_{model,i})^2)}{n}} \tag{2}$$

where, the values are defined as follows:

x_i, y_i	The values that were observed and forecasted, along with the residue correspond to the i[th] data point.
$\bar{x}$ & $\bar{y}$	The arithmetic means of those values
X_{obs}	Observed value
X_{model}	The forecasted values for the specific year i

An ANN is a short-term forecasting technology that is widely viewed as promising. Improved methods for greater effectiveness Although ANNs performed severely in some early research, especially in the generalization component, they showed improved results when dealing with massive datasets. In this case, BPNNs and functional networks should be avoided. The models can handle noisy datasets accurately, efficiently, and quickly. In contrast, the NARX network outperformed the BPNN network. Even so, incorporating autoregressive models could improve accuracy.

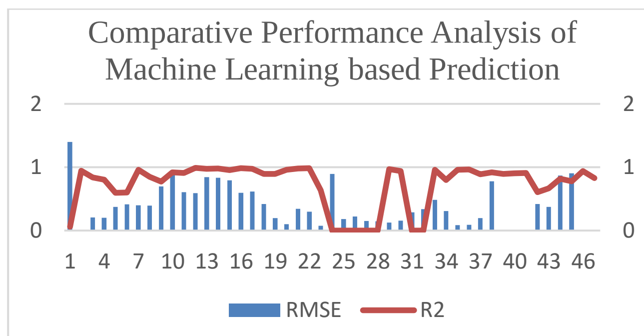

Fig. 10. Comparison of machine learning technologies in flood prediction based on R^2 and *RMSE* [20].

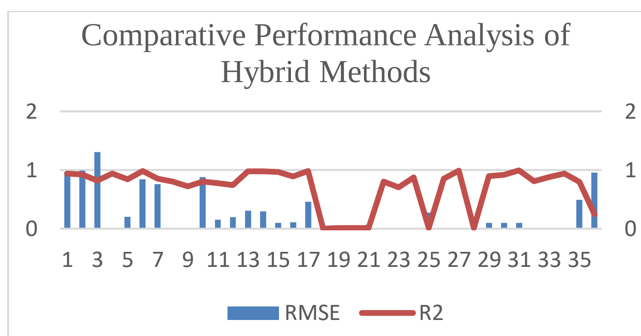

Fig. 11. R^2 and *RMSE* comparison of ML technologies in flood prediction [20].

TABLE II. A COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR FLOOD MODELING

Algorithm	*Description*	*Advantages*	*Disadvantages*	*References*
ANNs (Artificial Neural Networks)	Interpret historical data, build sophisticated and nonlinear models	Trustworthy data-driven tools	Network architecture limitations, inability to perceive the modeled system	[30]
MLP (Multilayer Perceptron)	FFNN with multiple layers, widely used in hydrogeological models	Simplicity, nonlinear activation, effectiveness	Challenging to optimize	[39]
SVM (Support Vector Machine)	Supervised learning machine based on structural risk minimization	Reliable and efficient, handles small sample and nonlinear problems	Dependence on training data quality, challenges in generalization	[29], [30], [31][32], [43] [8]
DT (Decision Tree)	The rapid algorithm, increasingly popular in ensemble models	Speed, suitability for flood modeling	Further research is needed for flood prediction	[30]
GA (Genetic Algorithm)	The survival of the fittest concept uses chromosomes and genes	Ability to search for optimal solutions	Dependent on suitable chromosome encoding	[47]

TABLE III. A SYSTEMATIC REVIEW OF KEY RESEARCH PAPERS FOCUSED ON FLOOD MODELING AND PREDICTION

Location	*Methodology*	*Results*	*Key Factors*	*Implications*	*Reference*
Kalvan watershed, Iran	Tested five ML algorithms (ERT, RRF, PRF, RF, BRT) with 15 climatic and geo-environmental variables	ERT yielded the highest AUC (0.82)	Topographical and hydrological parameters	Aid in flood mitigation planning	[43]
Various urban settings	Reviewed prevailing flood modeling approaches	Overview of methods for pluvial flood modeling	-	Guide urban flood managers in selecting appropriate methods	[44]
Quannan area, China	Compared NBTree, ADTree, and RF methods using 13 flood explanatory factors	RF demonstrated high accuracy for flood susceptibility assessment	Multiple environmental factors	Support flood prediction in the study area	[45]
Khiyav-Chai watershed, Iran	Employed MDA, CART, SVM, and ensemble modeling with various factors	MDA had the highest predictive accuracy (89%)	Slope, drainage density, distance from river	Identify flood-prone areas for prevention	[46]
Various urban areas	Summarized calculation methods for urban flood numerical simulation	Identified trends for improving model accuracy and computational efficiency	1D-2D coupling, finite volume method, unstructured meshing	Guide hydrologists in model selection	[47]
Damansara River catchment, Malaysia	Combined FR approach with SVM using 13 flood conditioning parameters	Effective for flood risk management along an expressway	Environmental parameters	Replicable in other areas for flood risk assessment	[48]
Various locations in Thailand	Used MIKE-11 hydrologic model and ML techniques to improve runoff forecasting	Enhanced flood prediction accuracy	Hydrological data	Real-time flood prediction for better management	[49]
Jakarta, Indonesia	Utilized environmental factors and satellite imagery	Supported flood susceptibility prediction for flood risk management	Environmental conditions	Effective flood risk assessment	[50]
Indian monsoon forecasting	Employed neural networks for ISMR prediction	Demonstrated superior accuracy over existing models	Indian monsoon data	Improved ISMR forecasting	[51]
Various locations	Utilized various ML models for flood prediction	Compared models to improve prediction accuracy	Environmental and hydrological data	Enhanced flood prediction for management	[52]

Overall, the single prediction models examined could produce reasonably accurate short-term forecasts. However, hybrid models such as ANFIS and WNN scored better for forecasts lasting more than two hours. Non-linear and actual flood predictions were made more accessible and accurate with SVR-tuned advanced ANFIS hybrid models.

The capacity of (ML) models to capture the intricate (potentially unknown) nonlinear interactions between predictor (input) and predict and (output) variables sets them apart from other hydrologic modeling techniques, which solely base their predictions on previously observed data. Another benefit of these flexible models is their relatively high computational efficiency, which has increased their appeal over the past 20 years because of the continuing advancements in computing power [20].

Table III provides a comprehensive overview of various studies that have employed these approaches, encompassing a diverse range of locations and methodologies. The studies demonstrate the effectiveness of ML algorithms in improving flood prediction accuracy, emphasizing the importance of environmental and hydrological factors in flood susceptibility assessment. Furthermore, the table highlights the development of various modeling techniques for urban flood modeling and the potential of integrated approaches combining ML and traditional methods for enhanced flood risk management. These findings underscore the transformative role of ML and other advanced techniques in addressing flood-related challenges, paving the way for more effective flood preparedness and mitigation strategies.

VII. Analytical Discussion

This systematic review offers valuable insights into the state of the art in flood modeling and prediction, providing a foundation for informed decision-making in flood risk management and urban planning. It underscores the potential of machine learning techniques in enhancing the ability to predict and mitigate the impacts of flash floods and pluvial flooding in urban areas. The study also highlights the strengths and weaknesses of both hydrologic models and data-driven machine learning models, paving the way for potential hybrid modeling approaches that can provide more accurate and efficient flood management strategies.

Additionally, the review identifies trends in research focus and geographic areas, which can guide future research directions and flood management efforts. Overall, this comprehensive analysis contributes to the ongoing efforts to develop effective flood control measures and adapt to the increasing challenges posed by climate change and urbanization.

Regarding computed water surface elevations and flow/stage hydrographs, 1D modeling can be just as accurate as 2D and 3D modeling while requiring less computational time and effort. The following are some examples of where this might be possible:

Rivers and floodplains where the predominant flow and force directions and paths follow the overall river flow. For most river systems, this is believed to be true, despite debates about the influence of lateral and vertical velocity on predicted water surface heights as well as the flood inundation boundary.

Gravity-driven streams with sloping beds tend to have very little overbank area. According to the river’s dams, levees, pumping stations, and bridges, the river’s predicted level and flow are affected by these gated projects.

The hydrologic flow characteristics present in many of the river systems are something that no 2D model has been able to represent adequately. It is a case where 1D models are much ahead of 2D models in terms of technological sophistication. These characteristics can be implemented in 2D models, but a popular 2D model with such a comprehensive collection of features is yet to be developed.

Medium to big rivers are considered when modeling a significant portion of the river system (100 or more miles) (i.e., 2-week to 6-month forecasts). Even with multi-processor computing and GPU (Graphics Processing Units) computation, 2D models have substantial geographical and simulation time restrictions regarding real-time forecasting. This is going to change over time. There is no evidence to justify using a 2D model in these situations. Many of the benefits of a 2D model will be thwarted by inaccurate topographical data due to a lack of information in the overbank and channel bathymetry.

As a result, the correctness of a 1D or 2D modeling approach for a given application is frequently in question. It is not as simple as choosing whether to solve the Saint Venant equations in one or two dimensions. There are other variables to consider. It was concluded that there are knowledge and tool gaps when determining whether to employ 1D, 2D, or 3D. It is necessary to use 1D and 2D models in the modeling efforts, and Hydrologic modeling software must be improved in this area.

Le et al. [38] [39] proposed many ANNs for seasonal flood forecasting and compared the outcomes. Data from 1970–1985 was employed as a training tool, while the 1986–1987 dataset was used to verify the results. The ANNs were able to identify whether the dataset was incomplete accurately. According to [20], employing ANNs to speed up data analysis could lower analytical expenses. ANNs have also been used to create precipitation forecast models, as seen in the [40]. An ANN model was used for a historical dataset spanning the years 1900–2001 to evaluate prediction accuracy. For this dataset, more than 100 floodstream localities were examined. The ANN, on the other hand, had issues with generalization. Despite this, water management found the ANN to be helpful in this instance.

Prediction models for heavy rain and flooding were developed by [37] using a variety of BPNNs. This dataset covered 1871–2010, and it did so every month. It was discovered that BPNN models using virtual networks were ideal for nonlinear flood forecasting since they were both fast and resilient. The following source may be long-term flood projections: BPNN and LLR-based models were used by Shamim et al. [41] to explain nonlinear floods better. An estimated two decades' worth of rainfall, evaporation, and water level statistics stretches back to 1988 in this dataset. According to their findings, LLR outperformed the BFGSNN neural network model in terms of efficiency and durability. In contrast to the other approaches, BPNN performed well.

According to [20], the most reliable ANN for long-term flood prediction is the BPNN model. For the long-term forecasting of flood discharge, ANNs performed better than BPNNs and MLPs in reference. There were promising outcomes while employing MLP. There was, however, the problem of generality. Mulualem and Liou [40] used an SVM model to forecast streamflow and reservoir inflow long-term. For comparison, they used neural networks and ARMA. Monthly river-flow flows from 1974–1998 were used to train the models, and data from 1999–2003 was used to evaluate them. According to a comparison of model performance, SVM outperformed the ANN when predicting long-term discharges.

ANNs are the most extensively utilized ML tool for dealing with complex flood features and incomplete data sets because of their accuracy, high fault tolerance, and parallel solid processing. ANN, on the other hand, has a problem with generalization. In [30], ANFIS, MLP, and SVM outperformed ANNs. As suitable data pre-processing, wavelet transformations may increase the performance of most machine learning (ML) methods, which have been suggested. WANs, as opposed to traditional ANNs, have few benefits.

According to Hosseini et al. [42], short-term and long-term rainfall-runoff models' accuracy, precision, and performance were all improved by deconstructing ML algorithms (such as WNN). However, while WNNs have proven a success, long-term forecasts are limited. Hybrid WNN/autoregressive models WMRA and WARM were developed to improve the precision of one-year-ahead forecasts.

Through deconstruction, models performed far better in some circumstances, resulting in more accurate results. For example, wavelet–neuro-fuzzy models outperformed standalone ANFIS and ANNs in terms of accuracy and speed [42]. However, as the lead time lengthened, so did the degree of uncertainty in the predictions. Future research should take into account the accuracy of the model. An essential part of developing hybrid techniques was using data decomposition methodologies such as autoregressive, wavelet transformations (DWT), wavelet–autoregressive, IIS, and EMD.

Extrapolative prediction systems are another advancement in prediction accuracy and generalizability (EPS). Recent ensemble techniques have significantly changed speed, accuracy, and generality. Many non-traditional approaches to machine learning were used in developing ANN and WNN model training algorithms, such as BB sampling and genetic programming, in addition to typical ML techniques like the basic average and Bayesian inference. Conversely, ensembles outperformed models that did not include human decision-making as an input component. New decomposition–ensemble prediction models appropriate for monthly forecasts were the most significant hybrid models. Their accuracy and generalization improved significantly compared to SVM, ANFIS, and ANNs.

Predicting floods using machine learning models is still a developing field. An overview of machine learning models used in flood forecasting is presented in this study, along with the development of a classification strategy to examine the literature. More than 6,000 items were analyzed and investigated in the survey. Several original and significant studies compared the precision of at least two machine learning models. Models were classified into two groups depending on the lead time, with hybrid and single-method subgroups further subdividing.

Considering performance comparisons from previous literature helped in accessing and analyzing how these approaches perform. All approaches were examined using R^2 and RMSE, as well as a generalization, robustness, and computing costs/speeds. Despite the previous optimistic results, there was a lot of research and testing to enhance and develop the most popular machine learning algorithms like ANNs and SVM, SVR and ANFIS, WNN, and DTs. Four essential topics emerged from the research on improving prediction models' accuracy and general models.

The initial stage was to use both conventional and soft computing in conjunction with at least two different types of machine learning algorithms. Secondly, data segmentation methods were used to increase the dataset's quality, resulting in much higher accuracy in the predictions made from the data. Generalizability and predictive power were significantly improved and decreased by employing several approaches. Add-on optimizer algorithms, for example, can be used to increase the quality of neural network models.

Flood prediction is projected to improve significantly in the near and long term due to the development of these four leading technologies. Developing these new machine learning approaches relies heavily on applying soft computing principles in algorithm design. As a result, future hybrid machine-learning methods will rely heavily on soft computing techniques, as detailed in the study.

VIII. Conclusion

In conclusion, the study has underscored the critical impact of floods on the environment, emphasizing the need for effective prediction models to mitigate their adverse effects, such as loss of life, crop destruction, and increased waterborne ailments. The investigation has focused on the application of one-dimensional, two-dimensional, and three-dimensional hydrologic modeling for flood hazard forecasting, providing valuable insights for the development of preventive interventions. Notably, the study has revealed the growing superiority of machine learning (ML) techniques over traditional hydrologic models in predicting flood occurrences.

The findings indicate that ML, armed with sophisticated algorithms and extensive datasets, excels in its ability to provide accurate flood predictions. Notably, the study suggests that ML models can offer effective solutions by correctly estimating complex hydrological parameters, as exemplified in the accurate determination of water flow through structures like the hydrologic manifold P-10. This superiority of ML over hydrologic modeling systems is further supported by the bibliometric investigation, which revealed a burgeoning interest in utilizing machine learning for flood prediction.

Two key recommendations emerge from this study to further advance flood prediction accuracy. First, there is a discernible shift toward the use of machine learning techniques, and it is recommended to collect real-world data on flood events from Jeddah municipality. This data would serve as a valuable resource for training machine learning algorithms, enhancing their accuracy and applicability in the specific context of the study. Second, acknowledging the need for a comprehensive approach, the study recommends developing a hybrid model that combines time-series data for machine learning-based algorithms with the expertise of 1D/2D/3D hydrologic modeling. This hybrid approach aims to leverage the strengths of both methodologies for improved flood prediction, acknowledging the importance of evolving hydrologic modeling science while embracing the advancements offered by machine learning.

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