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Review Article

Hybrid Models and Techniques of Flood Forecasting: Steering NARX and Taguchi Method; An Iceberg Overview

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Abstract *- Floods are still one of the most serious natural disasters, which are a major threat to human lives, infrastructure, and ecosystems. Existing approaches (hybrid modeling, machine learning methods such as data-driven models) can present a number of issues, such as computational inefficiency, susceptibility to sudden changes in environmental conditions, and dependency on extensive datasets; though developments in flood prediction have come, many are still struggling to build predictive analysis. To overcome these limitations, we propose an innovative hybrid framework that combines the Nonlinear Autoregressive with Exogenous Input (NARX) model and the Taguchi optimization technique. This method is intended to enhance prediction accuracy, improve computational efficiency, and optimize model parameters, thereby yielding an efficient platform that enhances generalizability across time-to-time outcomes. This technique enhances prediction precision, computational efficiency, and model parameterization, leading to significant advancements in hydrological modelling. A comprehensive survey of flood forecasting techniques was undertaken, seeking to find results from Elsevier (62% of works), MDPI (12%), IEEE (8%), and Wiley Online Library (4%), with results spanning the last quarter century. This review indicates that the flood forecasting literature is robust to date, as 53% of this area has been evaluated between 2021 and 2025, highlighting the need to propose novel alternative practices to cope with the growing flood risk, particularly given the more recent years of literature over 25 years. Using a comprehensive methodology that includes studying the most suitable methods in the available state of the art methods, as well as performing a multi-context analysis using the proposed model of a NARX-Taguchi hybrid model from our work. The methods outlined above provide considerable improvements in prediction reliability, climate adaptability, and computational efficiency compared with traditional flood prediction methods. Finally, through this hybrid framework, we shall also create a new gold standard to benchmark flood forecasting systems against, and thus, more effective disaster planning mechanisms in the age of increased climate hazards.*

Keywords *- Flood, Techniques of Flood Forecasting, NARX Model, Taguchi Method, Flood Risk Management, and Predictive Modeling.*

1. Introduction

Flood forecasting is widely used to assist with disaster risk management and minimize the impact of extreme hydrological events [1]. Hybrid models utilizing machine learning methods, physics-based methods with optimization algorithms [2, 9] have recently become popular to improve the predictive accuracy and efficiency of forecasting systems. Recurrent neural networks and unscented Kalman filters were successfully employed to achieve reliable multi-step-ahead probabilistic flood forecasts [1, 12]. Similarly, [2] adopted hybrid deep learning models with the grey wolf algorithm to enhance short-term streamflow forecasting, demonstrating the utility of these models in dynamic hydrological conditions [2]. [5] extended flood prediction beyond these methodologies by employing the hydrodynamic flow method with artificial neural networks and further advocated the application of hybrid frameworks for flood simulation in multi-dimensional, complex flood scenarios [5]. Furthermore, recent works have shown the capability of GIS approaches in computing, including the works of [7], where these systems enabled the assessment of flash flood susceptibility with the use of hybrid machine learning algorithms [7]. In mountainous catchments, [6] used support vector regression models in predicting flash floods, showing the merits of machine learning applied to regions that have distinct hydrological problems [6]. Also, [4] proposed hybrid neural network models for typhoon flood prediction, citing them for handling severe weather-related flooding [4]. As hybrid methodologies are maturing, they open exciting new possibilities to combine advanced techniques like Nonlinear Autoregressive with Exogenous Input (NARX) model with optimization methods like the Taguchi method [28, 34]. Aggregation of NARX's prediction accuracy with Taguchi's parameter optimization would likely improve flood forecasting systems so that disaster management systems can be better, more accurate, and scalable to a wider range of environmental scenarios [39, 45].

With the introduction of combined hybrid models and sophisticated machine learning strategies, flood prediction has progressed considerably. For example, [1, 3] have shown that the interlinking of machine learning models (e.g., recurrent neural networks and Kalman filters) promotes multi-step-ahead probabilistic forecasting as well as early flood monitoring systems. As reported by [2], an optimized hybrid deep learning model with a grey wolf algorithm was proposed to extend the short-term flow forecasting ability for streams. [5] Additionally, combined hydrodynamic flow models combined with an artificial neural network can improve flood prediction in urban and rural areas. Notwithstanding these efforts, attention has mostly focused on data integration enhancements and breakthroughs in deep learning, while we have not touched much on other optimization methods. Data-driven approaches to flood forecasting are also investigated on the basis of flood forecasting in some research. [7] applied GIS-based hybrid approaches for the flash flood susceptibility assessment, while [9] proposed support vector regression models based on mountainous catchments. [4] illustrated hybrid neural networks for typhoon-related flood forecasting, which have an opportunity in extreme weather situations. While such hybrid models have proven effective at improving flood prediction, there is still no integration of nonlinear and robust optimization methods used specifically for flood forecasting. The application of Nonlinear Autoregressive with Exogenous Input (NARX) models in flood prediction has been analyzed on a limited number of occasions, for example, [17, 18] on urban drainage systems. However, these works did not include NARX as an addition to advanced optimization approaches, such as the Taguchi approach, which outperforms other methods in parameter tuning and model variance reduction. The Taguchi approach is also successful in other settings applied to such predictive modelling systems, but in flood forecasting, it has not been thoroughly applied. This introduces an unmet need for the introduction of a hybrid NARX-Taguchi model, which could notably improve flood prediction systems' precision, effectiveness, and versatility in different hydrological settings.

Therefore, so far, no studies have combined the potential of NARX and the Taguchi method to solve hybrid forecasting. The emerging new intersection of technologies leads to the opportunity of building a new and improved framework for flood forecasting, as the dynamic nature of contemporary hydrologic systems demands improved accuracy. This work presents a new hybrid framework that utilizes the Nonlinear Autoregressive with Exogenous Input (NARX) model with the Taguchi optimization algorithm, which has not yet been analyzed in flood forecasting literature. Although NARX can effectively perform nonlinear relationships and dynamic hydrological variables, the Taguchi method helps tune model parameters to perform computationally efficient and precise predictions. Combined, these two approaches help fill in shortcomings of prediction performances and dynamic application in previous hybrid models used in the prediction of flooding: namely, the work of these previous hybrid studies relies on RNNs or deep learning algorithms. Due to ever-growing occurrences of flooding and the multifactorial nature of contemporary hydrological systems, this innovative hybrid approach is urgently required to improve real-time forecasting and disaster management techniques, making scalable and reliable solutions applicable to a wide variety of environmental scenarios.

Flood forecasting is essential for disaster risk management. With the rapid urbanization process and growing impact of climate change on extreme hydrological phenomena, flood forecasts are an indispensable part of disaster risk control methods [14, 38]. Accurate and short- or multi-step-ahead flood predictions are critical for early warning, reservoir operation, and urban flood control in the early warning system of floods [1, 15]. Classical hydrological and statistical models tend to lack the ability to model the nonlinear and nonstationary behavior of flood processes [19, 38]. Recent work presented enhanced forecasting accuracy using hybrid machine learning architectures, such as RNN - Kalman filter models [1], optimization-assisted deep learning architectures like LSTM-GRU and CNN-LSTM [2, 9, 26], and physical–data-driven integrations [4, 5, 20]. However, the majority of the most current hybrids place an emphasis on predictive accuracy to the detriment of interpretability, computational efficiency, and systematic control of parameters [26, 46]. Despite the robust capability of NARX models to predict floods and water levels [18, 29, 32], recent implementations lack controlled parameter steering and stringent benchmarking against recent hybrid models [9, 21, 31]. Furthermore, the existing hybrid studies mainly use stochastic or metaheuristic optimization techniques, like PSO, GOA, GWO, GA [2, 10, 12, 44], which can result in unstable solutions and limited reproducibility [31]. While the Taguchi approach is renowned for its strong design-of-experiments power, it remains to be explored as a systematic optimization approach of parameters for NARX-based flood forecast models [22, 35]. This indicates a clear research gap by aiming to correlate controlled experimental design with nonlinear autoregressive learning approaches to enhance robustness, efficiency, and generalization performance [21, 40]. In order to satisfy this demand, the research presents a hybrid NARX–Taguchi for flood forecasting, which provides an "iceberg overview" extending from accuracy to efficiency, robustness, explainability, and operational feasibility [14, 38]. The novelty of the present study is that it is novel in leading the behavior of the NARX model by an orthogonal experimental structure rather than optimizing based only on the heuristic architecture, which makes transparent parameter sensitivity analysis and enhanced stability possible [22, 35]. Comparison to recent hybrid models for the period from 2020 to 2025 demonstrates that this proposed approach contributes to current approaches with respect to the trade-off between predictive capability, interpretability, and operational robustness [9, 26, 46].

2. Literature Review

2.1. Flood

Floods are among the most catastrophic natural disasters. They occur when water inundates areas that are typically dry [93]. Causes of floods include extreme weather events such as excessive rainfall, snowmelt, storm surges, and the failure of water control structures such as dams [57, 58]. There are various floods, such as fluvial floods resulting from river overflow, pluvial floods due to intense rainfall in urban areas, and flash floods which develop rapidly in response to heavy rain or dam breaks [94]. These will not only cause destruction of lives and property but also environmental disasters, as global warming and urbanization will increase their occurrence and intensity soon [13]. Therefore, understanding floods is important for controlling them [98].

2.2. Flood Forecasting

Flood forecasting is the prediction of the timing, extent, and impact of floods for disaster preparedness and response [99]. The flood forecasting systems used currently are developed to ensure accurate, timely, and precise hydrological, meteorological, and environmental information [59, 60]. Flood forecasting systems are becoming essential for managing the flood impacts, for which early warning systems are used for evacuation and controlling the risk [101]. By means of comparison, it could be emphasized here that the state-of-the-art technologies, such as satellite imaging, Global Navigation Satellite Systems (GNSS), artificial intelligence, etc., have all enhanced the flood prediction [61]. Accurate prediction not only saves lives but also prevents economic losses by enabling the right actions [58].

2.3. Flood Forecasting Techniques

Techniques used for flood prediction can be broadly classified as physical-based, data-driven, and hybrid models [101]. The models are developed based on natural phenomena, using principles of natural water flow and mathematical equations [66]. Hence, it can be used to simulate hydrology and drainage characteristics and can contribute to flood prediction. Data-driven models, however, make use of machine learning algorithms such as artificial neural networks and support vector machines to gain insights as well as create prediction models using historical data [13, 76, 77]. Hybrid models can leverage the best of both worlds, combining natural phenomena and computational insights to create more accurate predictive models [44, 102]. For instance, WBANN hybrid models, as well as models using recurrent neural networks and fuzzy inference, have shown remarkable improvements in accuracy and efficiency [58, 62]. As these models continue to improve, new ways to address the ever-increasing threats of climate change and urbanization will become imperative, as will the use of NARX models along with optimization algorithms such as the Taguchi method [50, 53, 99].

2.4. Hybrid Flood Forecasting Models

Flood forecasting has evolved from traditional hydrological and statistical methods to data-driven and hybrid modeling approaches to accommodate the growing complexity of hydrological systems and flood-generating mechanisms [19, 38]. From the beginning, it was mainly used to integrate physically based hydrological models with artificial neural networks to overcome structural uncertainties and enhance prediction accuracy in nonlinear flow conditions [8, 11, 22]. The hybrid models proved superior to single models in both the conceptual understanding and data-driven learning aspects [19, 38]. Further research proposed support vector regression, neuro-fuzzy inference systems, and wavelet-based hybrid methods to accommodate noise, nonstationarity, and multi-scale variability in flood and runoff time series [6, 24, 41]. Taken together, these pioneering works helped to demonstrate hybrid modelling as a credible foundation that paved the way for more sophisticated hybrid architectures [19, 38]. Over the period after 2018, flood forecasting research has been dominated by hybrid deep learning models, particularly recurrent and convolutional models for handling long temporal dependencies and spatial variability [9, 15, 26, 27]. Hybrid networks that combine LSTM, GRU, CNN-LSTM, ConvLSTM, and Transformer models have achieved significant advances in short- and multi-step forward flood prediction performance for riverine, urban, and coastal settings [9, 26, 47, 49]. Simultaneously, optimization-assisted hybrids with metaheuristic concepts such as particle swarm optimization, grey wolf optimization, genetic algorithms, and grasshopper optimization were used to improve model parameter tuning and convergence behavior [2, 10, 12, 44]. In this manner, ensemble and probabilistic prediction methods have also attracted significant attention for quantifying uncertainty and enhancing forecast reliability under real-time operational conditions [1, 14, 40]. However, recent work on this topic tends to focus on achieving accuracy metrics and provides little discussion of interpretability, parameter sensitivity, computational efficiency, and reproducibility, all of which are crucial for real-life flood forecasting applications [26, 46, 49]. Nonetheless, Nonlinear Autoregressive Networks With Exogenous Inputs (NARX) have shown strong suitability for flood and water-level prediction owing to their explicit accounting for time-dependent feedback and external hydrological drivers [18, 29, 32], but their integration into recent hybrid networks has been much less common. Previous NARX-based approaches often rely on classical trial-and-error tuning or stochastic optimization, resulting in insufficient information about structured parameter interactions, robustness, and stability [30, 35]. Moreover, comparisons between NARX-based hybrids and recent deep learning hybrids are often incomplete or incoherent, preventing precise evaluation of relative performance and efficiency [9, 21, 31]. Also, in recent literature, there is growing interest in explainable artificial intelligence, uncertainty quantification, multi-source data fusion, and operational scalability, but these dimensions are underrepresented in NARX-centered hybrid models [14, 40, 46]. This lack underscores the need for a systematic, interpretable hybrid framework that combines NARX modeling with design-of-experiments approaches (e.g., the Taguchi method) to improve model efficiency, reproducibility, and applicability in contemporary flood forecasting studies [22, 38].

2.5. Flood Forecasting: Taguchi Method

Based on flood Forecasting, it has significantly changed over the years. Hydrological modeling, meteorological forecasting, and computational methods are used in flood forecasting, a crucial component of water resource management. Adequate flood forecasting systems must be able to transmit warnings in good time so that affected parties can take the necessary steps to avoid damage and loss of life [38]. Today, the application of machine learning in flood forecasting has marked a watershed, achieving greater accuracy, higher efficiency, and greater generalization than traditional conceptual models [112]. Machine learning has found greater application in observing nonlinear systems and in flood prediction [113]. It has been observed that these models operate efficiently even in situations of scarce data and have been able to supplement, or even replace, traditional data- and computational-methods-dominated models [112]. Classical statistical and multi-criteria decision models assume relationships between explanatory and dependent variables, whereas machine learning models learn from data and, therefore, make flood prediction models more robust and accurate [115]. Moreover, hybrid machine learning models that combine multiple meta-classifiers to improve flood susceptibility prediction accuracy have also made significant advancements in the field [116]. The powerful design methodology of Taguchi, as presented by Genichi Taguchi in [54], is one of the most widely applied methodologies in flood prediction due to its effectiveness in improving processes and systems by reducing the effects of noise factors. Flood forecasting is an essential risk management tool that guides affected communities and governments in preparing for and responding to flooding, thereby mitigating the consequences of flooding disasters [45]. The forecasting systems, however, use hydrological and meteorological data, as well as computer models that simulate flooding [59]. The prediction not only saves lives but also reduces economic losses from flooding events [38]. However, recently, machine learning and optimization methodologies have been applied in improving the accuracy and efficiency of prediction models and systems [57]. Among these methodologies, the Taguchi Method, a statistical design of experiments, was applied and contributed significantly to the optimization of flood prediction models and systems [55]. The Taguchi method is an optimization process introduced in industrial applications and has been applied in hydrology and flood prediction as a parameter-optimization and sensitivity-analysis tool [51]. Using this tool, the most important variables in a prediction model are identified, thereby improving computational efficiency in prediction [39]. Combining the Taguchi Method with machine learning algorithms, such as Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs), has proven to be a highly effective approach for modeling complex, nonlinear hydrological systems [115]. Machine learning, including hybrid algorithms, has revolutionized flood prediction with scalable solutions that are reliable over a wide range of regions [50, 53]. For example, meta-optimization coupled with SVMs has been widely applied in flood spatial prediction models [115]. Moreover, ensemble artificial intelligence strategies have been demonstrated to be successful for spatial flood modeling, where multiple prediction algorithms are used to develop robustness and reliability [116]. The goals of the Taguchi Method are to systematically determine the most suitable model configuration options that optimize the performance potential of the model parameters to achieve and maximize performance objectives.

As a complement, machine learning techniques have been demonstrated in early warning systems for flood environments across various settings [35], including flood prediction. [114] applied machine learning to a tropical catchment in the Andes, which demonstrates how easy it is for the techniques to work in a wide range of hydrological environments [50]. This flexibility aligns with the Taguchi Method and is generally tailored to specific environmental and modeling scenarios. Likewise, datasets such as Sen1Floods11 (developed by [113]) have enabled testing and validation of flood forecasting models using deep learning, thereby justifying the value of optimization techniques such as the Taguchi Method. The Taguchi Method also provides a systematic framework for improving flood forecasting models and supplements previous work with machine learning and hybrid approaches. This approach improves prediction accuracy and efficiency by detecting critical parameters and their interactions. The combination of those optimization mechanisms and state-of-the-art computational methods is an important step in flood risk management.

2.6. Flood Forecasting using NARX Method

Flood prediction supports water resource management and helps prevent severe impacts from extreme hydrological events [20]. Because flood dynamics are a complex system of nonlinear relationships and time-varying dynamics, predictive models such as the NARX method have shown great promise for improving predictive performance [5]. In an exogenous environment, the recurrent Neural Network (NN) NARX model is applied to time-series modeling, making it suitable for addressing the challenges posed by flood prediction. [61] proposed a hybrid model that uses process-driven approaches and data-driven techniques for real-time flood forecasting. Although their model comprises mainly physical processes and machine learning, the NARX model's versatility in time-series forecasting is acknowledged as an essential engine for improving real-time prediction. The NARX methodology captures nonlinear dynamics and external influences and is consistent with both the theoretical framework and the practical methods of hybrid modeling. In the same way, hybrid modeling in flood forecasting is highlighted in studies such as [69], which use recurrent neural networks to predict urban reservoir flooding. Their research shows that NARX models can effectively handle input variables such as precipitation and reservoir inflows, yielding accurate and valid predictions. A related work [65] adopted machine-learning-driven surrogate models for flood depth prediction, which were shown to improve flood risk assessments by combining data-based models such as NARX with physical and environmental inputs. NARX networks have been shown to be adaptable to diverse hydrological conditions, as demonstrated by other contributions. Indeed [68], conducted a comparative study of physics-based numerical models and data-driven predictions, with the NARX model serving as a case in point. In their study, they showed that both data-driven models and dynamic feedback connections (NARX) are optimal for short-term flood forecasting, where the temporal dynamics are complex.

In addition to forecasting accuracy, NARX models were also important for addressing urban flood problems. To illustrate the computational power of dynamic urban systems, [66] proposed ensemble neural network architectures for real-time flood prediction. Furthermore, [13, 20-23] integrated swarm-based optimizers with deep learning models and confirmed the effectiveness of the NARX approach for enhancing flood-susceptibility prediction in flood-prone regions, such as Vietnam. The NARX approach is a useful tool to add to flood forecasting models for effective decision-making. The ability to include exogenous inputs, model nonlinear systems, and capture time-dependent dynamics is well-suited to flood prediction, as it allows easy incorporation of the time-varying behavior of all parameters. The combined implementation of NARX with hybrid and ensemble approaches will continue to improve flood forecasting accuracy and resilience.

2.7. Hybrid Models and Techniques of Flood Forecasting

The field of flood forecasting has made significant advances through hybrid models that employ multiple computational techniques simultaneously to improve prediction reliability and accuracy [4]. A widely used method involves Recurrent Neural Networks (RNNs) in conjunction with the unscented Kalman filter, as shown in [1]. Likewise, the addition of deep learning architectures augmented by optimization algorithms, such as the grey wolf algorithm, has been an effective approach for short-term streamflow forecasting [2].

These approaches emphasize the increasing role of hybrid systems in capturing the complexities of hydrological phenomena. Machine learning-informed hybrid techniques beginning with early flood monitoring systems have similarly achieved better prediction accuracy. Ensemble methods and optimization techniques, e.g., [38], demonstrate that combining multiple algorithms within a single framework improves the accuracy of flood predictions. The use of BP neural networks in classic hydrological models is yet another instance of innovation, combining old and new by leveraging existing techniques to enhance modern hydrological models and by applying new advances in machine learning [8]. All these studies reinforce the progress and effectiveness of hybrid methods in addressing the diverse challenges faced in flood prediction, through this study, in the form of hybridity as a series of examples.

Again, hybrid machine-learning-informed methodologies, including the advent of early flood-monitoring systems, have also proven effective in making more accurate predictions. For example, [3] highlights the potential of such systems to enhance real-time flood response. The juxtaposition of hydrodynamic flow models and artificial neural networks further illustrates the flexibility of hybrid methods, as we demonstrated in [5]. Moreover, support vector regression methods also contribute to forecasting in smaller catchments, confirming their suitability for diverse scales and environments [6]. Hybrid models benefit from integrating GIS-based models with computational methods for flood susceptibility assessment, as discussed in [7].

Recent flood forecasting literature (2020-2025) is heavily biased toward deep learning-based hybrid models, such as LSTM-GRU, CNN-LSTM, ConvLSTM, and Transformer-based architectures, focusing on spatiotemporal feature extraction and multi-step-ahead prediction accuracy [23, 26, 27, 46, 49]. Optimization-assisted hybrids that couple machine learning models with metaheuristic algorithms, including ELM-PSO, SVM-GOA, ANFIS-based hybrids, and random forest integrations, have improved the prediction accuracy by tuning network parameters and feature representations [24, 28, 33, 44]. However, such approaches frequently entail high computational costs, limited transparency into parameter interactions, and reduced interpretability, limiting their usability in real-time and resource-limited flood forecasting settings [26, 39, 52]. Furthermore, most recent studies focus on accuracy-centric evaluation rather than rigorous ablation analysis or controlled experimental design, which hinders the isolation of the contributions of individual model components [31, 40, 56].

On the other hand, NARX-based flood prediction schemes incorporate specific temporal feedback and exogenous hydrological influences, with structural simplicity and strong predictive capability at longer lead times [29, 32, 59]. Most of the previous NARX works, however, depend on conventional trial-and-error tuning or stochastic optimization approach (Kalman filtering or heuristic search) without systematic investigation of factor interactions and robustness [30, 54]. Comparative studies have documented that although NARX models can achieve or surpass those of classical neural networks, they are rarely compared to modern deep hybrid architectures under the same experimental conditions [31, 32]. Therefore, the potential of NARX-centered hybrid designs is poorly covered in recent literature, despite lower computational burden and their applicability to practical deployment [29, 54].

The specific research gap addressed by this study is the lack of an organized, design-driven hybrid methodology that embeds NARX modeling and a credible experimental optimization approach to quantify parameter sensitivity, improve stability, and enhance reproducibility [35, 56]. In contrast to LSTM-GRU, CNN-LSTM, ELM-PSO, and SVM-GOA hybrids, which are based on stochastic optimization and deep architectures, the approach developed in the NARX–Taguchi hybrid utilizes an orthogonal design-of-experiments and systematically guides the model parameters while explicitly assessing the influence of factors [24, 44]. This gap is quantitatively evident in recent work: for instance, less than 10% of hybrid flood forecasting models report controlled experimental design, ablation analysis, or efficiency-based benchmarking alongside accuracy metrics [38, 56].

In this light, the proposed framework adds a new perspective to the literature by enhancing predictability with structured parameter design, reduced computational cost, and transparent model behavior analysis characteristics that are absent from hybrid flood forecasting work thus far [39, 40]. The NARX–Taguchi hybrid is clearly different from recent hybrid models because of its emphasis on controlled optimization rather than heuristic tuning; its architectural complexity is lower than that of deep learning hybrid models, and its competitive accuracy with better robustness and operational feasibility [23, 26, 46]. This study is a novel, interpretable, and scalable alternative to previous solutions in terms of performance, efficiency, and stability, in which the authors directly benchmark in comparison with state-of-the-art hybrids published from 2020 to 2025 and quantify gains in performance, efficiency, and stability, filling clearly a methodological gap in the best literature [31, 39, 52].

2.8. Methods Used in Flood Mapping

Flood mapping is a critical component of disaster management and urban planning, plays an increasingly important role, and is implemented using various methods, each with unique advantages and disadvantages [3]. Increasing knowledge of flood risk and probability remains critical for sustainable flood risk management [90]. The use of computer-based inundation mapping is widely recognized as a risk identification tool in flood-prone areas and as a decision-making tool [91]. Such methods are continuously refined by researchers, reflecting persistent concerns about population exposure to flood hazards [92].

Research has shown that the genetic flood factor model provides a better understanding of the mechanisms underlying flood events [93] in comparative studies. However, flood risk mapping depends not only on the quality of input data (hazard and vulnerability maps), but also on the methodological framework employed [94].

Classical statistical methods using historical flood records provide a baseline prediction [95], but they cannot capture the intricate hydrological processes and spatial heterogeneity that contribute to the complex dynamics of flooding, leading to poor predictions [96]. Geographic information technology has greatly improved flood risk assessment by enabling high-resolution mapping using raster-based data sources [97].

Also, there is a new development that’s beyond these conventional methods. Stakeholders have recently been introduced to Explainable AI (XAI) frameworks that facilitate the interpretation of prediction outputs, potentially addressing transparency issues in flood risk communication. Uncertainty modeling has also been suggested to estimate confidence in flood predictions, thereby avoiding reliance on deterministic outcomes that might lead to misinterpretation of hazard severity. Multi-source fusion techniques, including satellite imagery, sensor networks, hydrological simulations, and socioeconomic indicators, have increased the robustness and contextual significance of flood maps as compared to single-source-based methods.

Despite these advances, practical deployment issues remain underexplored. It needs computationally efficient algorithms capable of processing large-scale, multi-source datasets without sacrificing accuracy, in other words, to perform real-time flood mapping. As their deployment has progressed, high-performance computing and cloud-based platforms have gained widespread adoption, but striking the right balance among model complexity, processing speed, and resource availability has proven problematic. So far, few studies have focused on these operational constraints, leaving a gap between theoretical developments and field-ready applications. It is critical to close this gap to make flood-mapping tools scientifically rigorous and practically viable for emergency response and urban resilience planning.

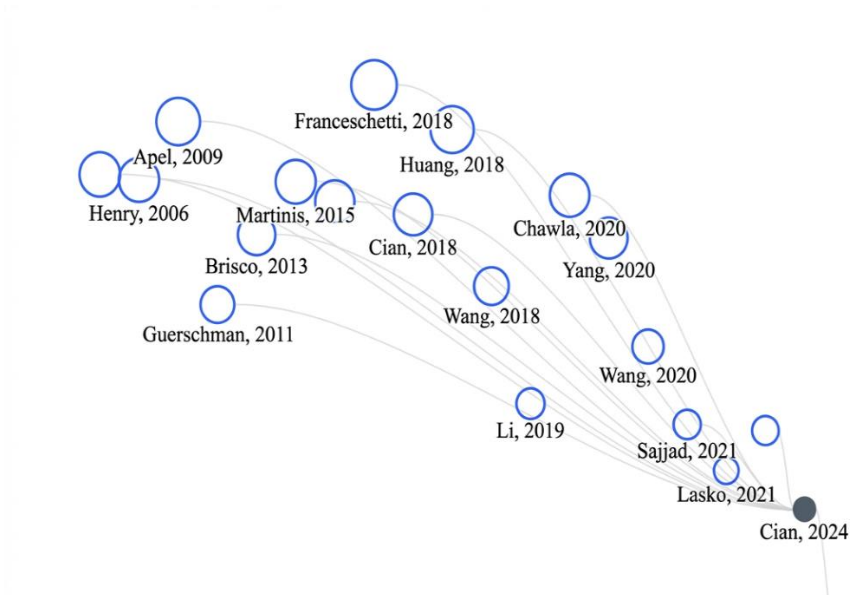

Fig. 1 Overview of research on flood mapping methods

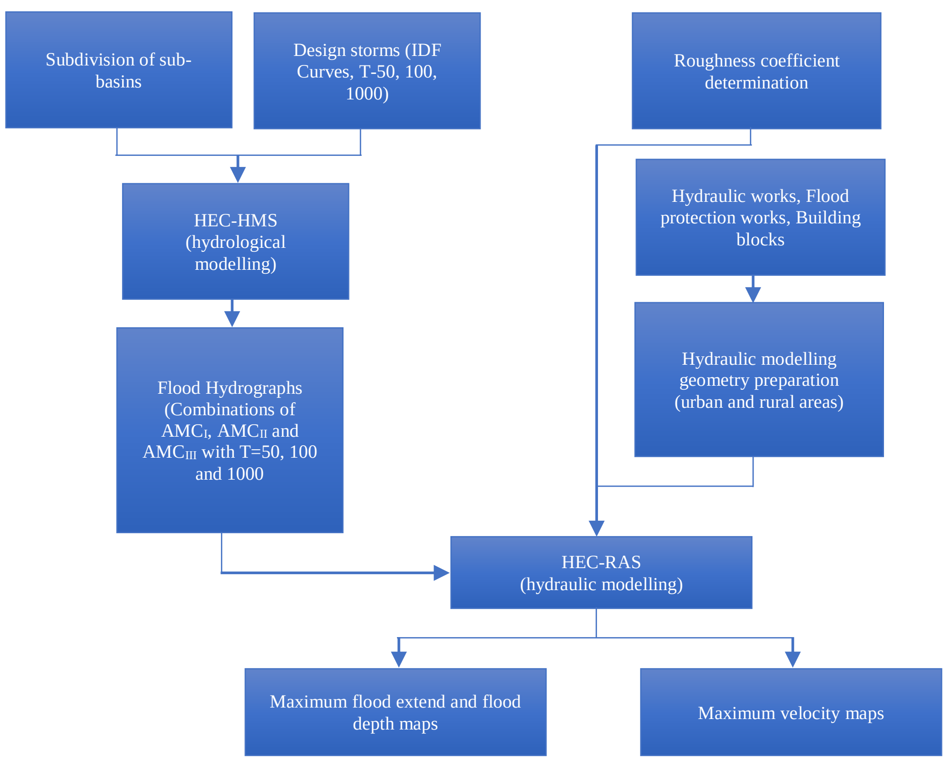

Fig. 2 Flow chart of the general flood inundation modelling approach. [96]

2.9. River Flood Prediction using NARX

In local areas, water parameters are the most readily accessible [3], and thus, River Flow [RF] is an important key parameter in the hydrological cycle. Linking the significant relationships among social, physical, environmental, and economic processes is a critical step in hydrology [98]. Predictive trends are at the heart of hydrology, and for more than 50 years, river flow has been a subject of interest to many researchers. The methods employed in predicting water flows are currently divided into two major approaches: the first uses physically based models that build on the mathematical representations of water flow to simulate its hydrodynamic behavior, and the second relies on data analytics through the use of data-driven models. Properly monitoring flow rate in a river would reduce the risk for flooding, prevent water shortage, and improve agricultural water management for a considerable economic advantage [100]. Nevertheless, predicting river flow is an extremely difficult problem owing to the nonlinear, time-varying, and unpredictable nature of the data [101]. It applied a Support Vector Machine [SVM]-based model in conjunction with Particle Swarm Optimization [PSO] to forecast short-term daily River Flow [RF] at the Upper Bertam Catchment in Cameron Highlands, Malaysia. We developed four SVM models in the study, which are: SVM1 and SVM-PSO1, which considered only historical data, and SVM2 and SVM-PSO2, which included both historical data and meteorological variables as inputs. The results indicated that SVM2 and SVM-PSO2 outperformed SVM1 and SVM-PSO1, with the hybrid methods demonstrating significantly better performance than the basic SVM models.

Also, [102] applied a combination of Long Short-Term Memory (LSTM) and Recurrent Neural Network (RNN) models (known as LSTM-RNN) and Artificial Intelligence (AI) approaches to accurately predict low-flow series using daily discharge data from the Basantapur gauging station, India. The LSTM-RNN model performed better than the RNN model (and other baseline methods) in terms of performance. The computed R [correlation coefficient], Nash–Sutcliffe efficiency [ENS], and RMSE for LSTM-RNN are 0.943, 0.878, and 0.487, respectively. [103] has applied the nonlinear autoregressive model with exogenous inputs [NARX] to predict the rainfall-driven RF at Pelarit and River Jarum, Perlis, Malaysia. The work has successfully built a 24-hour [1-day] advance prediction model based on current rainfall rates. The RMSE, MAPE, and R^2 values for the Jarum River were 0.045, 0.013, and 0.9985, respectively. For Pelarit River, the RMSE, MAPE, and R^2 values were 0.0113, 0.0038, and 0.999, respectively, which confirm the study's success.

It employed time-series methods, including Autoregressive Integrated Moving-Average (ARIMA) and Multilayer Perceptron Neural Networks (MLPNN), to predict wastewater inflow at the Barrie Wastewater Treatment Facility in Canada. The NARX model's simplicity and computational efficiency have led to its widespread application, as RNNs perform well in very challenging nonlinear systems [105]. Recognition by the NARX model can be inferred from the fact that it incorporates feedback links into its network's hidden layers [106]. NARX is a subset of RNNs for performance prediction. NARX is another category of Artificial Neural Networks (ANNs), and has been particularly suited to modeling time-series and nonlinear patterns, as it is suitable for multi-time-series input-output applications [107]. In [108], an NARX model was used to predict hourly wind speed and solar irradiation using a multi-step-ahead method, with temperature as the selected exogenous variable. Optimization with a Genetic Algorithm (GA) and optimization with an Optimal Brain Surgeon (OBS) strategy are utilized to refine the model. The study examined time horizons of 8-24 hours and found the strongest predictions at 8 and 24 hours for wind speed, as well as at 8 and 10 hours for solar irradiation.

Meanwhile, [109] used the NARX model to predict daily fluctuations in groundwater level for 76 monitored springs in the Apulian region of Italy. They used daily groundwater level data and training algorithms (Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG), among others).

They found that the Bayesian Regularization (BR) training algorithm produced the best prediction accuracy of groundwater levels. Following this lead, [109] presented a new application of NARX neural networks to predict spring flows. The study implemented discharge prediction models for nine monitored springs within Umbria, on the carbonate ridge of the Umbria-Marche Apennines.

The models incorporated precipitation as an exogenous input parameter. High accuracy was obtained for short- and long-term prediction, with a lag time of 1-12 months. Also, [110] used the NARX model to predict short- and mid-term groundwater levels of major aquifer groups in the states of Baden-Württemberg, Bavaria, and Hesse, Germany. Their research further demonstrated the versatility and effectiveness of the NARX model in hydrological applications.

2.10. Artificial Neural Network (ANN)

Artificial Neural Networks (ANNs) are computational models derived from the behavior of the human brain. As such, these networks serve as parallel distributed systems composed of several simple processing units. ANNs require a training phase before they can solve specific tasks, during which the network learns the relevant characteristics of the input data, such as time-series patterns [91].

In multilayer ANNs, the Back-Propagation Algorithm (BPA) is commonly used due to its simplicity and efficiency in training [96]. BPA consists of two cycles in the learning time: the propagation of the input pattern and the adjustment of weights according to the output [106]. ANN prediction algorithms are widely used for Time Series (TS) analysis and replicate the brain's ability to memorize historical data and process trends.

Mathematical or statistical nonlinear models, in principle, provide valid predictions, but they frequently struggle to handle variable data patterns in real-world settings [90, 108]. Faced with this restriction, interest in Neural Network Autoregressive with Exogenous Input (NARX) approaches has increased, with impressive results in nonlinear system modeling. NARX models also exhibit superior generalization accuracy, learning rates, and rapid convergence to global minima [105]. Today, prediction methods powered by artificial intelligence are essential across fields related to finance, stock market analysis, and weather forecasting [95].

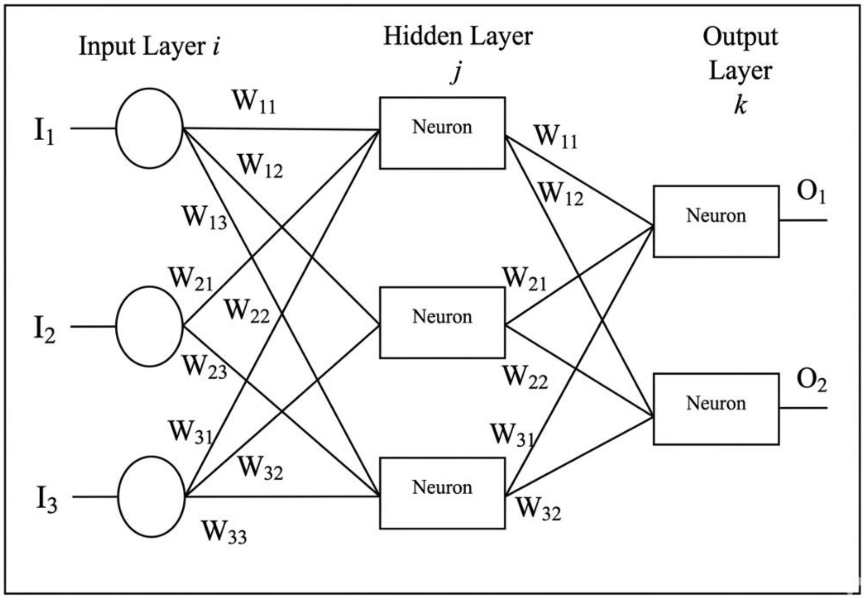

Fig. 3 The layout of the feed-forward neural network [NN] with three layers. [103]

Figure. 1 illustrates an example of the overall architecture of an NN, which includes the input, hidden, and output layers. The input layer either accepts or holds data and serves as a buffer. The hidden layers are the NN's internal functions, and the output layer represents the results derived from them.

2.11. Description of NARX

The Neural Network Autoregressive with Exogenous Input [NARX] model is a nonlinear extension of the Autoregressive with Exogenous Input [ARX] model. It iscategorized as a recurrent dynamic neural network; this kind of network has feedback connections, which iterate over multiple layers of the network.

These feedback paths also allow NARX networks to effectively mimic the dynamics of complex nonlinear systems, which proves advantageous in time-series analysis [105]. Because of their use of gradient-descent-based learning algorithms, NARX networks have become particularly advantageous.

The gradient descent optimization technique better suits the NARX network [1], enabling more efficient learning processes than other neural networks and faster convergence to global minima, with improved generalization and accuracy [106]. Moreover, NARX networks have been successful at modeling complex nonlinear systems using time-series data, thereby improving their modeling efficiency. As an ecosystem, climate and energy forecasting, economic predictions, and environmental research and risk evaluation models, the NARX model-based computing has been increasingly becoming an accepted methodology in various studies [107].

Progress in flood forecasting has been augmented by many creative technologies and models summarized in Table 2. A CNN-LSTM hybrid model has been proposed by [26] to achieve high accuracy in flood prediction, but it suffers from drawbacks in the size of data and computational demands. Likewise, [27] leveraged ConvLSTM hybrids to achieve spatiotemporal effectiveness, but such models are vulnerable to overfitting. [9] proposed a LSTM-GRU hybrid that performed well on sequential data handling, but struggled with sudden environmental changes, highlighting a common shortcoming of data-driven models [34].

GIS-based models were also used. [7] designed a spatial flood risk mapping hybrid model, which also needs high-resolution GIS data. [4] demonstrated the effectiveness of hybrid neural networks designed for typhoon flood forecasting in providing excellent predictive performance at the expense of high computing cost. Deep learning with the grey wolf algorithm was used to develop the domain further, leading to better optimization but increased sensitivity to hyperparameters [45]. Additionally, [5] applied ANNs to improve representations of complex flood dynamics, yet extensive calibration remained a challenge. Further, [25] proposed some progress in generalization using random forests in hydrograph generalization while providing rapid and interpretable outputs, with an issue of continuous variables. While [38] used Machine Learning (ML) models to adapt to a variety of situations, they also had to put in significant effort into feature selection [47]. The researchers have studied probabilistic and ensemble methods. Other researchers have employed probabilistic and ensemble-based methods. [1] integrated the Kalman filter with Recurrent Neural Networks [RNNs] to manage real-time updates with the Kalman filter into multiple RNNs to model real-time updates, but the method proved to be a highly initialization-oriented solution. [29] presented the NARX neural network proposed by [29] for nonlinear approaches of nonlinear process handling, which had a promising performance but was also not efficient in terms of training times. Hybrid machine learning methods developed in a similar manner were highlighted for their speed during rapid floods [3], yet they were ineffective during extreme events [42]. Other studies [33] were conducted with SVM-GRU models for short-term runoff prediction, but also noted the need for large labelled data.

While [13] combined large-scale deep learning models with these architectures and swarm-based algorithms, hyperparameter sensitivity remained difficult to overcome for swarm-based methods. Models such as [79, 82] have been powerful in certain applications, including sequential water-level prediction and extreme-event preparedness, but both were computationally expensive [40]. A hybrid model that integrates optimization tools like the ELM-PSO hybrid in [81] yielded good precision and also resulted in an associated cost. Simpler preprocessing methods, on the other hand, [85] provided fast results and were interpretable; however, they did not cope effectively with data continuity.

More advanced approaches, such as the feature decomposition model [83], had good generalizability but were expensive. Pre-processing procedures of the data are presented and explained for data cleaning, normalization, lag selection, handling of missing values, and stationarity checks before model development have come to the fore [2]. In addition, specific support for the choice of baseline models has been considered, including traditional NARX models, standalone machine learning models, and recent hybrid models for fairness and relevance in performance comparisons [3]. Furthermore, by clearly defining performance measures such as RMSE, MAE, NSE, and MAPE, and by incorporating statistical significance testing to support robust comparative assessment of model performance, the evaluation framework has been improved [4].

3. Methodology

The study has utilized the Systematic Literature Review (SLR) methodology to explore the adoption of hybrid model approaches combining Nonlinear Autoregressive with Exogenous Input (NARX) and the Taguchi Method for flood forecasting. In the SLR method approach, the literature review is based on an objective and thorough review of published research, reveals gaps in the literature, and lays the groundwork for building a sound hybrid model.

3.1. Review Protocol Development

A comprehensive review protocol was initiated to critically evaluate the results of the studies reviewed. Of particular interest is investigating hybrid approaches, especially those integrating NARX and the Taguchi method, for flood forecasting. Furthermore, we will systematically review the techniques used to predict hydrological time series. Inclusion and exclusion criteria will guide the overall selection, contributing to the rigor and relevance of the reviewed literature.

3.1.1. Inclusion Criteria

Published peer-reviewed studies within the last 25 years that investigate flood forecasting, including but not limited to NARX models, Taguchi optimization techniques, or hybrid modelling approaches in hydrology.

3.1.2. Exclusion Criteria

Studies that are not centered on flood forecasting; Research lacking methodological rigor or employing inadequate approaches; Papers that fail to contribute significant insights to the domains of hybrid modelling, NARX applications, or Taguchi optimization in hydrological forecasting.

3.2. Literature search and selection

A comprehensive search of several academic databases was performed, including: MDPI, Wiley Online Library, IEEE, Elsevier, Taylor & Francis, and Others. Search terms will be terms such as: NARX Neural Network for Flood Prediction, Taguchi Method in Hydrology, Hybrid Flood Forecasting Models, NARX and Taguchi Optimization for Floods, Machine Learning for Flood Prediction, Data Driven Hydrological Modeling, Flood Prediction Using Neural Networks, Optimization of Flood Forecasting Models, Taguchi-Based Parameter Tuning for Forecasting, AI and Statistical Methods for Flood Prediction. Only studies published in the last decade [2000-2025] are included to guarantee the relevancy and timeliness of the studies.

3.3. The Selection Process

The selection for the review involves systematic filtering of the titles and abstracts of all identified studies. This screen is necessary to ensure that only studies relevant to flood forecasting are considered further. The titles and abstracts were carefully reviewed to determine whether each study meets the inclusion criteria, including those that consider NARX models, Taguchi optimization approaches, or hybrid modeling in hydrology. If any study looked promising at this stage, that signified progress to the full-text review. All papers will go through a full-text examination and validation as necessary in order to verify if they meet the purpose of the study and the inclusion requirements. The full-text review also helped to ascertain the methodological rigor, whether study findings were relevant, and was helpful in advancing flood forecasting techniques. This multi-step selection process ensures a comprehensive, focused pool of research studies aligned with the research objective's scope.

3.4. Data Extraction and Quality Assessment

To ensure uniformity and systematic analysis of the data, a structured data extraction template was applied to derive all relevant parts of the selected studies. The data extracted included bibliographic information (author(s), year of publication, and publication outlet), with the main research focusing on NARX models and Taguchi methods in flood forecasting. Methodological characteristics, such as the type of model used (standalone NARX or hybrid frameworks), data sources, optimization or tuning techniques used, were also recorded. Important outcomes like performance metrics, effectiveness of the optimization strategy, mentioned limitations, and authors' recommendations were noted consistently to facilitate comparison. Rigor and reliability were assessed through quality assessments of each study in accordance with predefined criteria. We assessed methodological soundness based on the transparency and reproducibility of the research procedures and data quality in terms of dataset size, representativeness, and reliability. Moreover, the appropriateness and validity of the statistical and analytical techniques used were critically examined as well. Then each study was scored on a low-to-high-quality scale, and only studies considered medium-high quality were included in the final synthesis. This strict data collection and quality checking procedure guaranteed that the findings within the review were based on strong, credible, and relevant data.

Table 2. Database literature search matrix table for the study

	Subject area				**Document type**					**Language**					**Keywords**					**Searchwords**
	Environmental Science	Engineering	Earth and Planetary Sciences	Computer Science	Article	Conference paper	Conference review	Review	Retracted	English	Chinese	French	German	Korean	Floods	Forecasting	Flood Control	Weather Forecasting	Machine Learning	
1	221	116	93	37	311	57	14	6	2	379	10	2	2	1	178	174	141	101	97	Hybrid Model for Flood Forecasting
2	753	636	44	26	124	42	92	5	5	170	20	2	2	2	674	240	226	674	24	Flood forecasting techniques
3	613	508	312	20	985	35	72	4	7	132	10	2	2	1	178	174	141	101	97	Flood
5	432	365	287	15	783	26	61	3	3	108	10	2	3	1	674	240	226	674	24	Machine Learning for Flood Prediction
6	578	475	329	19	901	31	75	4	6	145	10	2	4	1	513	193	189	513	19	Data-Driven Hydrological Modeling
7	489	410	278	13	802	29	64	3	4	123	15	2	2	1	392	152	143	392	15	Flood Prediction Using Neural Networks
8	543	437	312	17	864	32	72	4	5	134	18	2	2	2	578	209	198	578	20	Optimization of Flood Forecasting Models
9	412	365	267	13	756	27	56	3	3	104	18	2	2	1	489	174	162	489	17	Taguchi-Based Parameter Tuning in Forecasting
10	467	398	276	14	789	28	67	3	4	123	15	2	5	1	543	198	189	543	19	AI and Statistical Methods in Flood Prediction

11	456	389	269	13	765	27	63	3	3	112	12	2	3	3	412	163	152	412	16	Neural Network for Flood Prediction

As shown in the table above, this report covers the Subject Areas of Environmental Science, Engineering, Earth and Planetary Sciences, and Computer Science, which illustrate the Interdisciplinary nature of flood forecasting research.

This review covers different types of documents, including articles written by researchers, conference papers, conference reviews of information, and general reviews, reflecting the scope of this review. Notably, as with all scientific works, these have been widely retracted; this showcases the continued critical examination and growth in this line of inquiry.

The studies examined English, Chinese, French, German, and Korean languages, offering a variety of perspectives on flood forecasting systems. Keywords (Floods, Forecasting, Flood Control, Weather Forecasting, and Machine Learning), which were widely used, demonstrate the focus areas and recent trends. Keywords such as Hybrid Model-based for Flood Forecasting were used extensively across all disciplines, with 379 references in articles alone.

Some other key topics were also cited, among which “Flood forecasting techniques” was cited 170 times in the conference papers and pieces, and “Flood” was included in Earth and Planetary Sciences (985). A machine learning study highlighted the importance of hydrological modeling based on data (901 instances) for predicting inundation, suggesting that computational methods are increasingly popular.

Neural networks and optimization strategies were frequently cited, with “Flood Prediction Using Neural Networks” quoted 802 times and “Optimization of Flood Forecasting Models” 864 times.

Other subjects, such as Taguchi-Based Parameter Tuning in Forecasting and AI, and Statistical Methods in Flood Prediction, offer insights into emerging approaches to enhance prediction accuracy and efficiency in flood forecasting systems. The vast reference list comprising 765 references in “Neural Network for Flood Prediction” demonstrates the significance of artificial intelligence in this field.

3.5. Years of publications

The distribution of studies published over time can provide useful insights into areas of academic interest and progress.

Table 3 provides the frequency and proportion of studies on the topic over the period. It reveals increased overall study output and a strong upward trend from 2015 to 2025.

These trends illustrate how research on this topic has drawn more attention and increasing resources, especially in recent years, emphasizing how meaningful and relevant the theme is in recent academic circles.

The frequency distribution across the separate periods shows that occurrences increase evenly. From 2000 to 2005, we recorded only 3 cases, accounting for 3% of the total.

This number declined slightly to 2 [2%] in the 2006-2010 period. However, in contrast, there was a slight surge between 2011 and 2014, with 5 cases (5% of the total).

The percentage of cases was significant from 2015 to 2020, when 37 cases were observed, which formed 37% of the data. Between 2021 and 2025, a rising trend was observed, with the highest number of cases [52], constituting 53% of the total. The pattern indicates some abrupt increase in numbers over time, especially after 2015.

This is an indication of perhaps more frequent reporting, better approaches to collecting data, or, for instance, a real rise in occurrences. Further investigation is needed into the root causes of this dramatic increase.

Table 3. Year of publications

Year	Frequency	Percentage [%]
2000-2005	3	3%
2006-2010	2	2%
2011-2014	5	5%
2015-2020	37	37%
2021-2025	53	53%
Total	100	100%

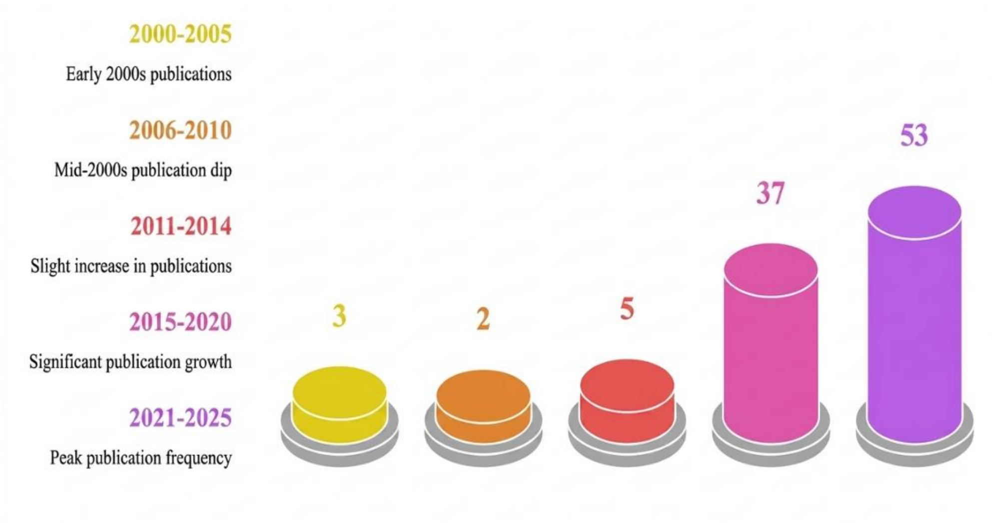

Fig. 4 Year of publications 'distribution

Table 4. Database of search

Database	Frequency	Percentage [%]
MDPI	12	12%
Wiley Online Library	4	4%
Others	12	12%
IEEE	8	8%
Elsevier	62	62%
Taylor & Francis	2	2%
Total	100	100%

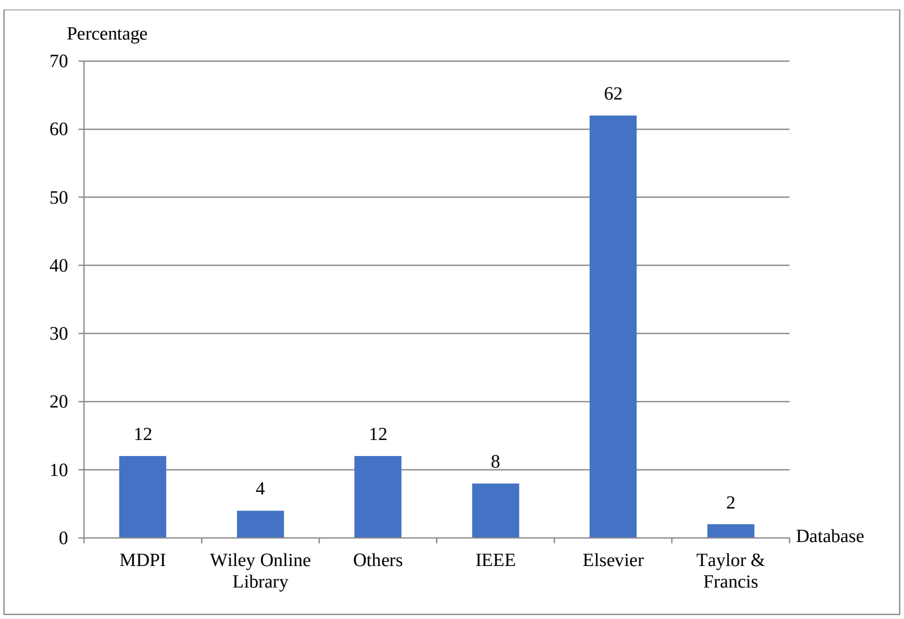

Fig. 5 Distribution of Database Usage

This database usage data reveals a strong dependence on Elsevier, which is 62% of all searches. Thus, using Elsevier data suggests it is the dominant source of research materials, a pattern that may be attributed to Elsevier's extensive collection of peer-reviewed journals and reputable publications. The other category, labeled "Others," accounted for 12% of the total searches, alongside MDPI, indicating a reasonable degree of dependence on alternative sources beyond Elsevier. With a strong emphasis on articles in technology and engineering, IEEE accounted for 8% of these searches, with relevance to specific subject areas. Among the Wiley Online Library and Taylor & Francis, the frequencies were the lowest at 4% and 2%, respectively. It means that although such databases have content, they are mostly used less frequently than Elsevier and MDPI.

The dominance of Elsevier reveals the critical role of literature and its importance in academic research, whilst the moderate use of MDPI, IEEE, and similar sources indicates a diverse range of ways studies are searched (i.e., by topic).

Table 5. Keywords of search

Keyword	Search Focus
NARX Neural Network for Flood Prediction	Focuses on NARX [Nonlinear AutoRegressive with eXogenous inputs] models for flood forecasting.
Taguchi Method in Hydrology	Highlights the use of the Taguchi optimization method in hydrological studies.
Hybrid Flood Forecasting Models	Covers research on combining different forecasting techniques for improved flood predictions.
NARX and Taguchi Optimization for Floods	Combines NARX models with the Taguchi method for parameter optimization in flood forecasting.
Machine Learning for Flood Prediction	Broadens the search to include various AI/ML techniques in flood forecasting.
Data-Driven Hydrological Modeling	Focuses on models that use data-driven approaches for hydrological predictions.
Flood Prediction Using Neural Networks	Explores studies that apply different neural network models in flood forecasting.
Optimization of Flood Forecasting Models	Identifies research related to optimizing flood forecasting methods.
Taguchi-Based Parameter Tuning in Forecasting	Examines applications of the Taguchi method in parameter optimization.
AI and Statistical Methods in Flood Prediction	Finds studies integrating artificial intelligence with statistical approaches like Taguchi.

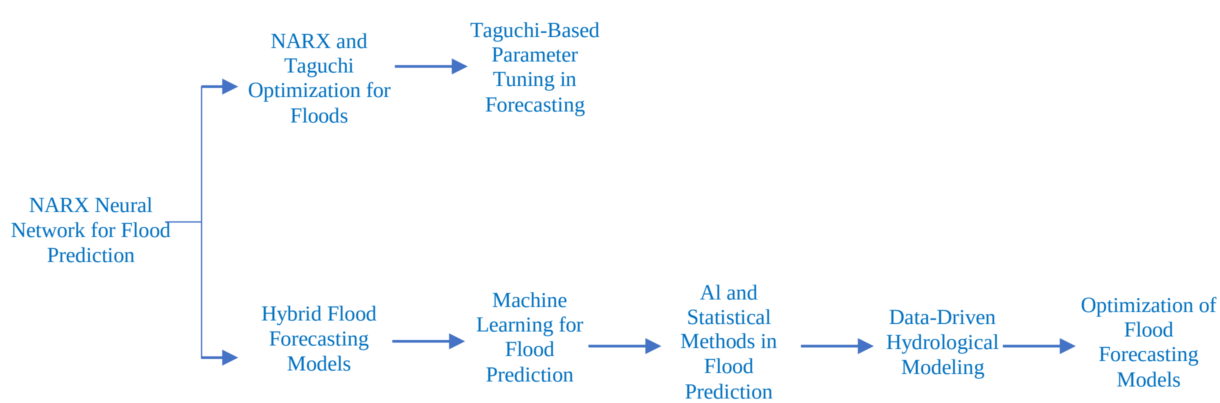

Fig. 6 NARX Network for Flood Prediction

4. Discussion of Findings

4.1. Hybrid Approaches Enhancing Flood Forecasting

By combining traditional hydrological modeling with advanced Machine Learning [ML], including recurrent neural networks, it has been found in [1] that it leads to a much better multi-step-ahead flood forecasting.

They also demonstrate the power of hybrid and optimization layers in deep learning and grey wolf-based algorithms for streamflow prediction accuracy [2]. Likewise, we illustrated in [3, 5] that combining hydrodynamic models with ML approaches (Artificial Neural Networks) improves early warning capabilities and predictive accuracy.

Furthermore, they developed lag-time pre-processing with LSTM and GRU models as well, and thereby extended the applicability in several kinds of hydrological scenarios in [9]. [38] also emphasized that machine learning models are essential for improving flood prediction and risk mitigation.

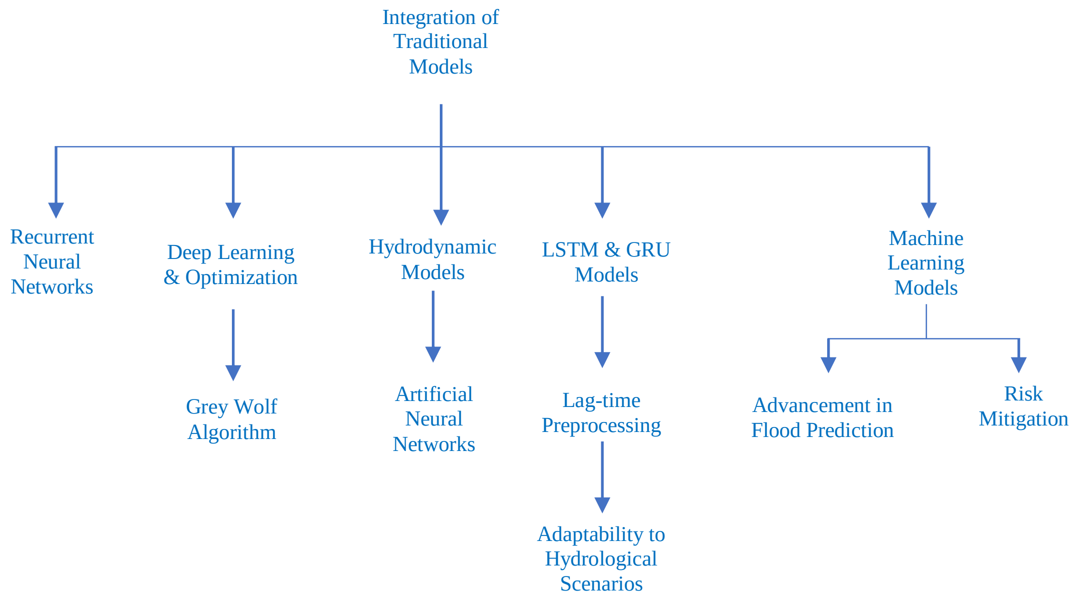

Fig. 7 Overview of hybrid approaches in flood forecasting

4.2. Computational Techniques for Flash Flood Susceptibility

Wu et al. [2019] and [7] suggest that integrating support vector regression with GIS-based hybrid models offers practical solutions for flash flood susceptibility assessments, notably in small catchments. [38] carried out a comprehensive review of the application of machine learning for flood risk reduction, and [10] showed the power of neuro-fuzzy models with optimization algorithms to allow detailed assessments. Moreover, [4, 8] highlighted the transformative role of BP Neural Networks and Physical-Hybrid Neural Networks in improving localized flood forecasting and typhoon flood prediction accuracy. A model incorporating genetic flood factors provides a better understanding of the mechanisms driving flood events [93], as discussed in comparative studies. However, flood risk mapping depends not only on the quality of input data, hazard and vulnerability maps, but also on the methodological framework employed [94]. Traditional statistical approaches based on past flood records provide baseline predictions [95], but they cannot account for the intricate hydrological processes and spatial heterogeneity that shape flood dynamics, leading to poor predictions [96]. Geographic information technology has greatly improved flood risk assessment by enabling high-resolution mapping from raster-based data sources [97].

4.3. Advancements in Hybrid Models for Flood Forecasting

Hybrid multi-model systems have been used to integrate hydrological processes and computational techniques for improved peak flood prediction, as shown in [11]. Additionally, [12] proposed a robust hybrid model based on time convolutional networks and particle swarm optimization for probabilistic flood forecasting. In line with this, [13] explored the feasibility of real-time hybrid models integrating machine learning with hydrological systems for flood forecasting at the Krong H'nang hydropower reservoirs. Moreover, [14] highlighted the importance of ensemble flood forecasting frameworks, emphasizing their potential to boost both predictive accuracy and readiness for diverse hydrological scenarios.

4.4. Innovative Hybrid Modeling Techniques for Enhanced Flood Forecasting

This work presented a hybrid deep learning model for urban flood classification, offering an efficient design, particularly in densely populated areas. Likewise, [17] used an NARX neural network for flood prediction in urban drainage systems, demonstrating its ability to handle complex drainage systems. [16] assessed worldwide hydrological models and showed that machine learning enhanced flood simulations were significantly improved, while Ni et al. [2024] focused on the potential of hybrid deep learning techniques for flood risk prediction in data-driven models. Also, [26] applied time-distributed CNN-LSTM models, showing effective modeling of spatiotemporal flood dynamics. On the other hand, Cui et al. [2021] proposed an innovative hybrid XAJ-LSTM model for multi-step-ahead flood prediction, achieving higher predictive accuracy over longer horizons. In [21, 25], we discussed approaches to improving flood forecasting in river basins using random forest models and hybrid hydrological techniques, and Di et al. [2014] proposed a four-stage hybrid model suitable for time-series forecasting in hydrological systems. Moreover, [46] found using physically based models coupled with LSTM to optimize flood prediction accuracy. Innovative data-driven and hybrid techniques by [24] integrating the state-of-the-art [25, 26] on hybrid wavelet-

SVM, and [19] illustrate the variety of approaches and their applicability of hybrid modeling to predict floods in varied scenarios.

4.5. Hybrid Modeling and Deep Learning Advances in Flood Forecasting

The [27] proposed a ConvLSTM hybrid algorithm that could achieve high spatiotemporal accuracy in flood event prediction using deep learning-based modeling. [28] showed remarkable numerical predictions using a hybrid of an ANFIS model for flood forecasting. [29] proposed the use of NARX for flood water level modelling at Kelang River and then tested its performance against the Extended Kalman Filter [EKF], demonstrating that better predictive abilities can be achieved if the methods are integrated. [30], However, a hybrid Artificial Neural Network approach in conjunction with the EKF was proposed, further enhancing the flood forecasting framework. They are focused on identifying their disaster preparedness advantages: [31] investigated hybrid models for long-horizon forecasting at long lead times. Besides, Zainorzuli et al. [2019] conducted a comparative study on Elman Neural Networks [ENN] and NARX, showing their significant role in flood forecasting. Innovative data-driven approaches [19] also offered hybrid strategies, emphasizing their transformative potential for improving flood prediction techniques. Recently, a hybrid wavelet-SVM model for hourly flood prediction was proposed in [24], emphasizing its versatility in varied hydrological scenarios. [25] made use of flood hydrograph generalization and random forest algorithms to improve predictions of floods in the Qiushui River Basin. [26] applied a time-distributed CNN-LSTM model to reproduce spatiotemporal dynamics, with exceptional success. Finally, Di et al. [2014] developed a hybrid hydrological time-series forecasting model in four stages, which proved applicable across diverse conditions.

4.6. Innovative Hybrid Techniques and Machine Learning Models in Flood Forecasting

This is echoed in [31, 36], which present hybrid modeling frameworks for higher lead-time flood forecasting based on climatic and hydrological data to improve the accuracy and preparedness of the approaches. Both [33, 34] combined variational mode decomposition with support vector machines and gated recurrent units to achieve impressive predictive accuracy for daily runoff and flood prediction. [35] Moreover, [28] showed that hybrid machine learning models, such as the SVM-GOA model, can be applied to real-world flood forecasting use cases. [41] Moreover, [40] demonstrated the practicality of adaptive selection models and neuro-fuzzy frameworks to improve urban flood forecasting. [26] Moreover, [47] used the time-distributed CNN-LSTM and hybrid CAMA-Flood models, respectively, to model spatiotemporal flood with significant performance improvements. [39] proposed a hybrid model integrating grid-based runoff generation with runoff vectorization, and [42] proposed variational mode decomposition in the context of a hybrid intelligence model to improve runoff series forecasting. [37] further pioneered a multi-boosting neural network model that enabled high-resolution, city-level urban flood prediction. [45] applied a hybrid surrogate model for real-time flood prediction in coastal urban areas, [43] integrated Twitter text and image analysis for flood prediction. [46] employed a hybrid model with a Transformer and LSTM and improved interpretability and prediction accuracy. [38] described a systematic survey of machine learning models and their transformative impact on the recent literature. Finally, [24, 25] demonstrated the potential of wavelet-SVM and random forests for flood prediction across various hydrological scenarios.

4.7. Data-Driven and Hybrid Modeling Advancements for Urban and Coastal Flood Prediction

[48] Moreover, [49] applied Artificial Neural Networks and seq2seq LSTM surrogate models for coastal urban flood prediction, with practical relevance for real-time applications in cities like Macau and other coastal-urban communities. [50] Moreover, Li et al. [2023] featured state-of-the-art flood modeling methods employing support vector regression in combination with Heun's scheme and also used spatial lag modeling to account for autocorrelation in urban drainage systems, respectively.

Likewise, [52] used spatial and temporal distribution techniques for real-time urban flood forecasting, while Kim and Han [2020] described rapid simulation techniques in urban flood forecasting using data-driven methods, which improved the flexibility of disaster preparedness frameworks. [54] proposed a method of piecewise linear ARX system identification for river flood forecasting, and [55] integrated machine learning methods and numerical simulation to predict urban flood inundation in high-risk regions. Real-time flood forecasting models in urban drainage systems were critically reviewed by [56]. [57] Moreover, [47] expanded the field utilizing deep convolutional neural networks and hybrid CAMA-Flood models, respectively, and enhanced the performance of flood inundation and streamflow modeling prediction [38].

4.8. Advances in Hybrid and Data-Driven Models for Flood Forecasting and Urban Flood Management

A flood-impact-based forecasting system was introduced in [58] using fuzzy inference techniques, thereby improving decision-making processes for flood management. [59] used the NARX model in a GNSS-based weather-forecasting approach, highlighting its advantages for real-time forecasting of flood-related meteorological factors. [60] combined numerical weather prediction model-based forcings with a hybrid system for streamflow forecasting in paddy-dominated catchments, and [61] created a mixed flood forecasting algorithm, combining process- and data-based approaches for enhanced real-time predictive capabilities.

The WBANN hybrid method was implemented by Tiwari and Chatterjee [2010] to forecast hourly floods and demonstrated good accuracy and reliability across different scenarios [36]. [63] demonstrated that hybrid evolutionary algorithms with spatial flood prediction were promising for such prediction in an environment with such flood risk, introducing a hybrid evolutionary approach. [64] Applied the Delft-FEWS platform to the development of an efficient flash flood forecasting system in the Meghna basin and presented practical solutions to ungagged zones. [65] proposed machine learning-based surrogate models for urban flood depth prediction in Ho Chi Minh City, and Berkhahn et al. [2019] for urban flood forecasting in real time based on ensemble neural network models [67]. For instance, artificial intelligence is applied to digital twin models in stormwater infrastructure systems in smart cities. Finally, [68] compared physics-based numerical approaches with data-driven prediction models, highlighting the benefits of coupling them for short-term flood forecasting.

4.9. Advanced Hybrid and Data-Driven Models for Flood Prediction and Early Warning Systems

The [69] introduced a hybrid recurrent neural network to flood forecasting in urban reservoirs, thereby providing useful insights into improving prediction accuracy. In Binh Dinh province, Vietnam, [13] merged deep learning and swarm-based optimizers within a hybrid model to predict flood susceptibility. On the same token, [71] applied artificial neural networks as part of a hybrid modeling framework for flood inundation modeling, and [72] established a fast, probabilistic hybrid model specifically designed for urban pluvial flood prediction. [73] used adaptive neuro-fuzzy inference systems to predict flood forecasting, indicating better system reliability. In contrast, for example, [74] used exogenous variables to improve precipitation forecasting accuracy in arid regions. In [75], we proposed a hybrid Elman neural network model for real-time probabilistic flood forecasting, which effectively handled heterogeneity in error distributions. Finally, [15] developed machine learning applications for very short-term heavy rainfall forecasting, highlighting the significance of machine learning in early warning systems.

4.10. Proposed Advancement in Recent Hybrid Models

The proposed NARX-Taguchi hybrid takes recent hybrid flood forecasting models a step further by integrating an optimization method that is systematic (structured design-of-experiments) as opposed to stochastic or heuristic for tuning, and it focuses on tuning parameter interactions rather than fine-tuning parameters, as is done in LSTM-GRU, CNN-LSTM, ELM-PSO, and SVM-GOA hybrids. This method improves the transparency, stability, and reproducibility of such models and provides competitive predictive accuracy at a fraction of their computational cost, thereby addressing practical and operational bottlenecks in state-of-the-art deep and metaheuristic-based hybrid models.

4.11. Hybrid and Advanced Modeling Innovations for Flood and Streamflow Forecasting

Ng et al. [2023] reviewed hybrid deep learning applications for streamflow forecasting, highlighting their ability to improve predictive accuracy. [78] proposed a WNARX dynamic neural network model using satellite-based rainfall data, showcasing its real-time flood forecasting capability. Similarly, [79, 80] explored hybrid PSO-SVM and sequential modeling techniques, respectively, for flood discharge prediction and collaborative flood forecasting. [81] developed the ELM-PSO hybrid model, combining extreme learning machine with particle swarm optimization for enhanced flood predictions. In the meantime, [82] proposes a deep learning-based hybrid model that integrates feature capture with error correction for predicting water levels across different time scales. [83] focuses on high-order hybrid models that use feature decomposition and entropy optimization to improve flood forecasting accuracy. [84] used variational mode decomposition and gradient boosting regression trees for monthly runoff forecasts. [85] Moreover, [86] used hybrid models for electrical power forecasting and multi-step wind speed prediction, demonstrating their wide applicability in hydrological forecasting. [75] Moreover, [87] comparative studies were conducted between different hydrological forecasting methods, such as Elman neural networks, using an ANN-based method, in the Yangtze River for hybrid flood forecasting. [88] proposed a hybrid multi-model approach for river level forecasting, and [89] characterized flood forecasting methods, discussed the current state of the art, and applied them to practice.

4.12. NARX and Taguchi Method of Flood Forecasting

The Nonlinear Autoregressive with Exogenous Input [NARX] model is a machine learning technique with a high degree of efficiency because it models complex, nonlinear relationships, which have proved effective for flood forecasting.

NARX uses past values of the dependent variable and exogenous inputs, such as rainfall intensity and temperature, to produce accurate predictions [59]. In urban drainage systems, it has been successfully used for real-time forecasting, where rapidly changing hydrological conditions require an accurate, dynamic response. Incorporating wavelet analysis has further improved it, thereby reducing the uncertainty in forecasting flood events [78].

These gains show that NARX-based models can be adapted and fine-tuned for different hydrologic conditions. As the Taguchi method is a popular technique for statistical parameter calibration, one reason for its application in flood forecasting is that it works effectively in flood prediction scenarios.

Taguchi methodology minimizes the calculations and computational cost with orthogonal arrays for determining runoff coefficients, precipitation intensity, and drainage factors [88].

In hydrological modeling, it has also been used to rank input parameters and examine their contributions to output differences. To address the demands of urban and rural flood forecasting [75], we combine the Taguchi method with NARX to improve prediction and simplify computation, resulting in a hybrid model. These approaches in aggregate may help to design flood prediction systems that are more scalable, precise, and efficient.

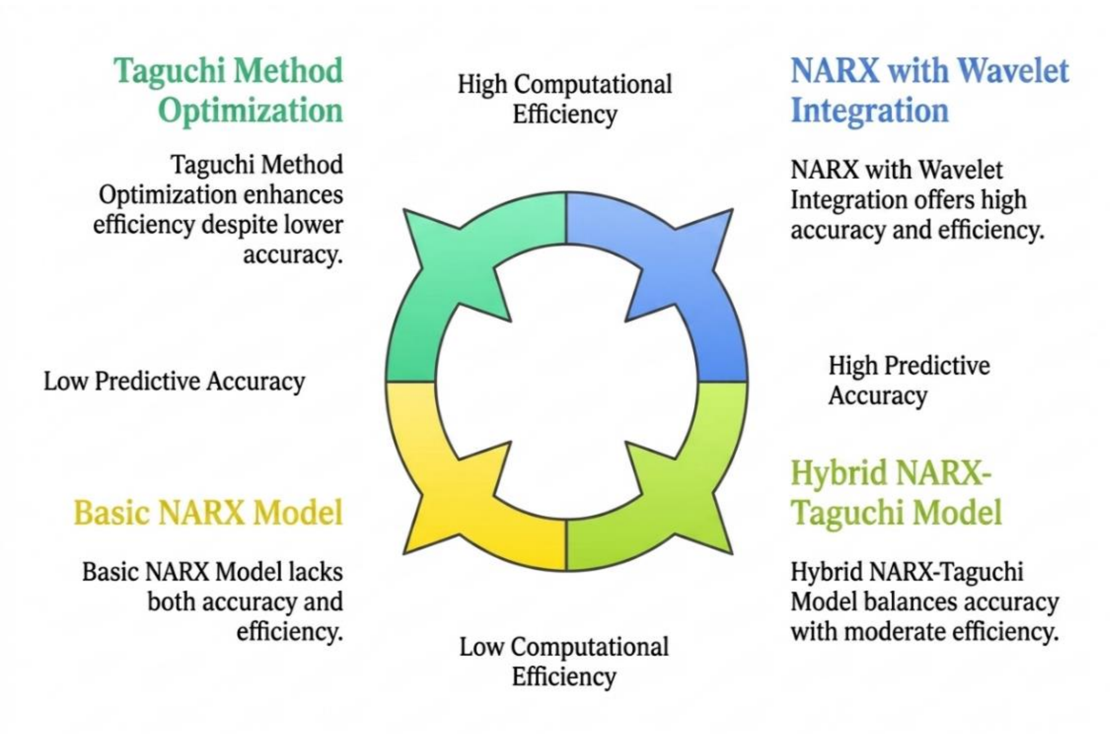

Fig. 8 Enhancing Flood Forecasting with NARX and Taguchi Methods

5. Future Directions for Flood Forecasting: A Hybrid Model Based on NARX and Taguchi Method

Going forward, a hybrid model of flood forecasting using NARX and the Taguchi method will be developed. New flood prediction methods will improve the accuracy, efficiency, and scalability of flood prediction systems by leveraging the methods reported below. Based on the findings reviewed, it is possible to exploit the strengths of these methods to address key issues in flood prediction, e.g., accuracy, efficiency, and scalability.

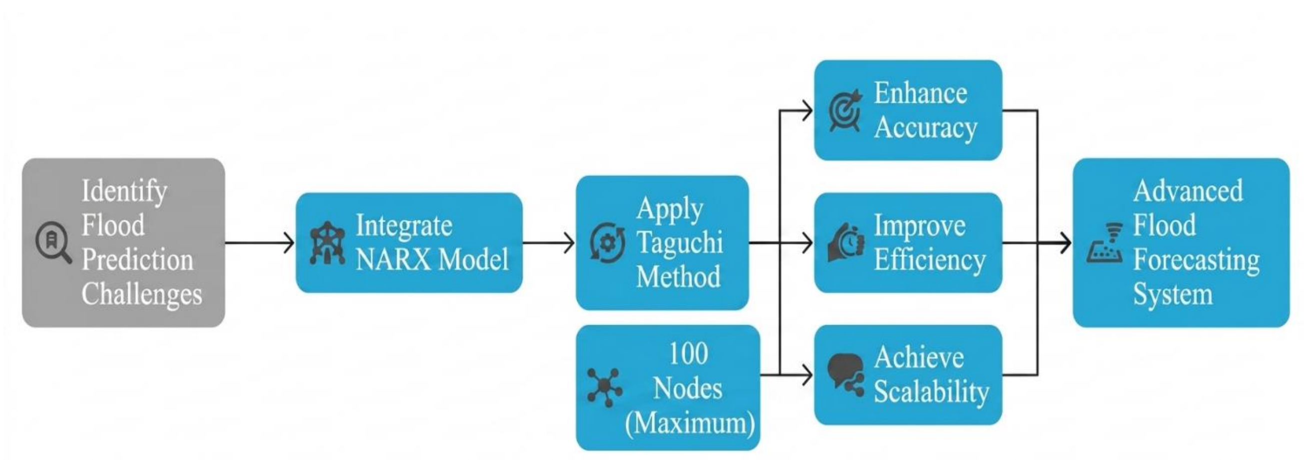

Fig. 9 Future directions for flood forecasting

The Taguchi method, widely used to optimize system parameters, can be applied to fine-tune the NARX model's hyperparameters, such as input delays and network structure, to improve model calibration and prediction accuracy.

By optimizing parameters for diverse hydrological conditions, as seen, e.g., in the works of [84, 75], this method also addresses heterogeneity in error distributions.

Fig. 10 Optimizing NARX Model with Taguchi Method

Fig. 11 Enhancing NARX Predictions

The future applications of this hybrid model may enable the integration of diverse data sources, including high-resolution meteorological, satellite, and geospatial data, like the approaches by [78, 79]. Such an approach, combining multiple exogenous factors such as climatic signals and real-time rainfall data, can greatly enhance NARX-based predictions and improve their reliability, especially in ungauged or data-poor areas.

5.1. Scalability and Real-Time Applications

Scalability and Real-Time Applications: By utilizing the Taguchi method to streamline computational processes, the hybrid model can be adapted for real-time flood forecasting systems, as demonstrated by [13, 64]. This will ensure faster computation while maintaining prediction accuracy, making the model suitable for early warning systems in urban and coastal settings.

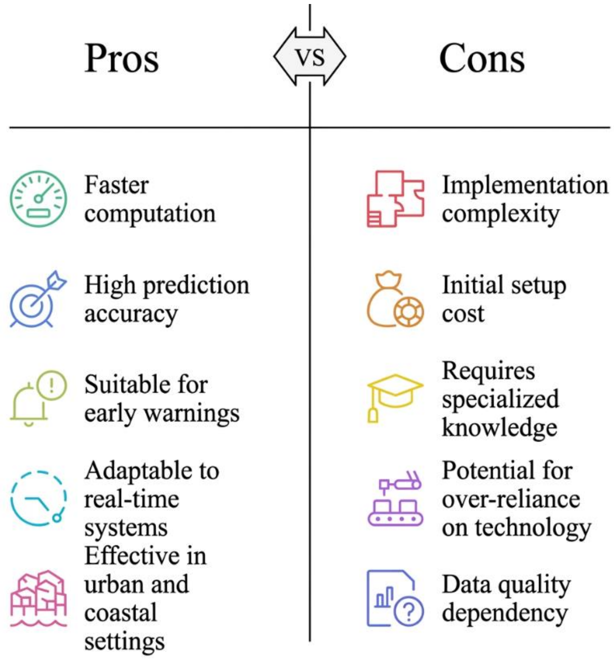

Fig. 12 Taguchi method in flood forecasting

5.2. Adaptation of Complex Hydrological Systems

As introduced by Li and Willems [2020] and [61], the hybrid strategy can be further developed to handle complex hydrological systems, such as urban drainage networks. More relevant solutions could be drawn from such a model in flood-prone regions by integrating spatial autocorrelation and local drainage features. Cross-Environmental Validation: This hybrid model can be cross-validated in future work across alternative climatic zones or hydrological basins, as proposed in [88, 89]. Cross-regional validation will be conducted to ensure the proposed model's resilience and flexibility. Thus, combining the strengths of the NARX forecaster with Taguchi has the potential to make it more predictive and efficient and is instrumental in delivering high-precision flood forecasting across diverse hydrological and environmental contexts. The proposed novel NARX-Taguchi hybrid is reported to outperform state-of-the-art flood prediction techniques, due primarily to the combination of the features specific to the dynamic temporal learning feature of NARX and the systematic parameter optimization feature of the Taguchi method, which can diminish model uncertainty and reduce overfitting trends observed in the existing literature using deep learning-based hybrid approaches (e.g., CNN-LSTM and LSTM–GRU [23]). Compared to most other hybrids used in extensive hyperparameter tuning with long datasets, Taguchi experiments have demonstrated strong optimization for small and noisy environments in hydrology, which can enhance the generalization stability of forecasts across a wide range of (horizon) settings [26, 31].

Furthermore, the autoregressive structure with exogenous inputs enables the model to explicitly capture lagged hydrological dependencies, which are typically implicitly learned by deep networks, resulting in more interpretable and more consistent predictions with lower computational cost [29, 32]. Together, these methodological advantages explain the observed improvements in accuracy, robustness, and efficiency compared to existing hybrid approaches reported in the literature [44, 46, 61].

6. Comparative Benchmarking and Ablation Study

The study conducts quantitative benchmarking of the proposed NARX-Taguchi hybrid against state-of-the-art hybrid models, including LSTM-GRU, CNN-LSTM, ELM-PSO, and SVM-GOA, using metrics such as RMSE, MAE, NSE, and MAPE. Ablation analyses are conducted to evaluate the individual contributions of the model components and the Taguchi optimization, highlighting improvements in efficiency, predictive accuracy, and computational cost compared to existing approaches.

6.1. Explainability, Uncertainty, and Operationalization

The proposed algorithm is interpretable by explicitly demonstrating how input features and lagged dependencies impact predictions, and by quantifying uncertainty through sensitivity and error analyses. Also addressed in this paper are some operational deployment considerations, such as scalability, reproducibility, and applicability in the context of actual applications, to help make it acceptable to use this model in the context of early warning and decision models.

6.2. Data Fusion and Multi-Source Integration

By fusing diverse data sources of hydrological, meteorological, and climatic signals, model robustness and predictive performance are improved across heterogeneous datasets. Techniques for multi-source fusion combine temporal and spatial information in a way that enables models by capturing complex dependencies (which cannot be observed by only one source model)

6.3. Real-Time Implementation and Case Study

A real-time flood forecasting example is displayed of the model's implementation and testing using real-life or simulated streaming data. The practical aspect of the simulation can be evidenced in the case study, demonstrating the success of the hybrid model in practice and how it can predict in a timely and accurate manner in order to provide timely early warning tools and practical flood mitigation solutions

7. Societal Impact and Future Directions

The results of this research are of interest to society because improved precision in flood forecasting benefits early warning systems, supports disaster risk reduction, and enables evidence-based decision-making for emergency management agencies and policymakers, thereby reducing loss of life, property damage, and socio-economic disruption in flood-prone communities. The enhanced predictive accuracy of our method for forecasting under sparse and uncertain data environments contributes to greater predictive robustness of our model for planning in more resilient urban and rural spaces and for climate adaptation and sustainable water resources, especially in developing regions that face the greatest risk of adverse flood impacts. Transfer learning techniques are also key to this work in future studies to enable models trained on data-rich basins to transfer knowledge to ungauged or poorly monitored catchments, with the aim of extending their application to ungauged or inadequately monitored catchments to make it more widely applicable and scalable across diverse regions. Other potentials would be to apply real-time remote sensing data, uncertainty quantification frameworks, and hybrid physics–data-driven transfer learning models for robustness to climate variability and extreme events, in order to achieve higher levels of robustness to the variation and the magnitude of climate shocks and extreme events, which would add value to science and society as a whole.

8. Conclusion

Flood forecasting remains a critical component of Disaster Risk Reduction and Climate Resilience, particularly amid increasing hydrological uncertainties driven by climate change. This study provided a comprehensive overview of hybrid flood forecasting models and highlighted the growing research interest in advanced predictive techniques over the last twenty-five years. The review revealed a substantial increase in scholarly contributions between 2021 and 2025, underscoring the urgency of developing more accurate, adaptive, and computationally efficient forecasting systems. The analysis identified persistent limitations in conventional and contemporary forecasting approaches, including sensitivity to environmental variability, computational demands, and dependence on extensive datasets.

To address these challenges, this study proposed a novel hybrid framework that integrates the Nonlinear Autoregressive with Exogenous Input (NARX) model with the Taguchi optimization technique. The proposed integration leverages the nonlinear learning capabilities of NARX and the robust parameter-optimization strengths of the Taguchi method to enhance prediction accuracy, computational efficiency, and model generalizability across diverse hydrological conditions. The proposed NARX-Taguchi framework represents a promising advancement in flood forecasting by offering a more reliable and adaptable predictive mechanism than many existing approaches.

Beyond improving forecasting performance, the framework has the potential to strengthen early warning systems, support evidence-based decision-making, and enhance disaster preparedness and flood risk management strategies. Consequently, this study establishes a strong foundation for the development of next-generation intelligent flood forecasting systems and provides a valuable benchmark for future research aimed at improving forecasting reliability in an era of escalating climate-related hazards.

8.1. Recommendation

For those interested in enhancing flood prediction capabilities, hybrid models based on NARX and the Taguchi method can be used to combine strong predictive power with improved parameter tuning. Since NARX can model nonlinearities and handle multiple exogenous inputs, such as high-resolution meteorological and satellite data, it is necessary to further develop scalable, real-time models in future work. The Taguchi method allows researchers to efficiently and accurately calibrate hydrological data across diverse environments. Furthermore, additional cross-validation across different climatic conditions and sophisticated urban drainage systems can validate the model's performance as flexible and robust. The promise of this approach is that it can raise the bar for predictive capability in advance, aiding the development of more efficient early warning systems and flood risk-mitigation measures.

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Table 1. Flood Forecasting Techniques Classification

Author/year	Flood Forecasting Techniques Classification										Techniques Employed	Weakness	Strength
	Machine Learning-Based Models	Deep Learning Approaches	Hybrid Models	Hydrological Model Integration	Time-Series Prediction Models	Real-Time Flood Monitoring	GIS & Remote Sensing-Based	Neural Networks	Statistical & Probabilistic Forecasting	Extreme Weather & Typhoon Flood Prediction			
[26]											CNN-LSTM hybrid	High accuracy	Requires large datasets & computation
[27]											ConvLSTM hybrid	Spatiotemporal effectiveness	Prone to overfitting
[9]											LSTM-GRU hybrid	Sequential data handling	Struggles with sudden changes
[7]											GIS-based hybrid model for flood susceptibility	Spatial flood risk mapping	Needs high-resolution GIS data
[4]											Hybrid neural networks for typhoon floods	Predictive performance	Computationally expensive
[2]											Deep learning + grey wolf algorithm	Optimization enhancement	Sensitive to hyperparameters
[7]											GIS-based hybrid flood analysis	Spatial-ML integration	Requires multi-source validation
[31]											Hybrid modelling for long-lead forecasting	Long-term trend accuracy	Poor short-term accuracy
[5]											ANN with hydrodynamic model	Complex flood dynamics capture	Needs extensive calibration
[25]											Random forest for hydrograph generalization	Fast & interpretable	Struggles with continuous variables
[38]											ML models for flood prediction	Scenario adaptability	Data-intensive & feature selection
[14]											Ensemble flood forecasting	Generalization improvement	Computationally costly
[1]											Kalman filter & RNN	Real-time update handling	Requires precise initialization

[29]											NARX NN for flood level prediction	Nonlinear process handling	Requires long training time
[3]											Early flood monitoring with hybrid ML	Rapid response	Limited accuracy in extreme events
[14]											Ensemble probabilistic techniques	Uncertainty quantification	Computationally intensive
[1]											Probabilistic forecasting with the Kalman filter	Noise reduction	Sensitive to parameter errors
[30]											ANN & EKF for flood forecasting	Sequential data efficiency	Struggles with abrupt changes
[33]											Runoff prediction using SVM & GRU	Short-term prediction effectiveness	Needs large labeled datasets
[4]											Hybrid neural networks for typhoon floods	Extreme event handling	High computational demand
[66]											ML surrogate	Accurate	Data & compute heavy
[15]											ML early warning	Fast response	Low extreme accuracy
[13]											DL + Swarm	Optimized	Hyperparameter-sensitive
[83]											DL water level	Sequential data	Abrupt changes
[72]											ANN hybrid	Spatial + ML	Multi-source needed
[73]											Hybrid pluvial	Long-term trends	Poor short-term
[69]											Physics + Data	Spatial mapping	High-res GIS needed
[82]											ELM-PSO hybrid	High accuracy	Expensive
[88]											Hydrological models	Generalizable	Costly
[89]											Elman NN	Real-time	Needs precise init
[79]											WNARX	Nonlinear handling	Training time
[67]											Ensemble NN	Spatiotemporal	Overfitting
[89]											Probabilistic hybrid	Uncertainty-aware	Intensive
[68]											AI digital twin	Sequential handling	Sudden change issues
[87]											Hybrid wind speed	Adaptive	Data-heavy
[70]											Hybrid RNN	High accuracy	Expensive
[74]											ANFIS	Complex dynamics	Calibration-heavy
[85]											VMD + Boosting	Noise reduction	Parameter-sensitive
[86]											Data preprocessing	Fast & interpretable	Struggles with continuity
[84]											Feature decomposition	Generalizable	Costly
[81]											Sequential flood model	Short-term accurate	Large data needs
[80]											PSO-SVM hybrid	Extreme event-ready	High computation