Metaheuristic Optimization Review

ISSN: 2692-4048 Vol: 05, No. 02, 2026 PP. 64–77
Article DOI: https://doi.org/10.54216/MOR.050205

REVIEW ARTICLE

Exploring the Synergy of AI-Driven Rainfall Forecasting and XR Technologies for Enhanced Water Resource Management: A Comprehensive Review

Mahmoud Elshabrawy Mohamed[1,*] **Abdelaziz Rabehi**[2,*]

[1] Computer Science and Intelligent Systems Research Center, Blacksburg 24060, Virginia, USA
[2] Telecommunications and Smart Systems Laboratory, University of Djelfa, PO Box 3117, Djelfa 17000, Algeria

Emails: mshabrawy@jcsis.org · Abdelaziz.rabehi@univ-djelfa.dz

Received: August 02, 2025 Revised: October 16, 2025 Accepted: December 07, 2025 ⋆ Corresponding author

ABSTRACT

Rainfall detection and forecasting are complex tasks in hydrology due to the nonlinear and multi-scale nature of precipitation processes. Recent advances in artificial intelligence (AI), deep learning, and metaheuristic optimization have significantly improved predictive accuracy across diverse geographic and climatic conditions. Deep learning models, such as ConvLSTM and hybrid CNN–LSTM systems, excel in capturing spatial and temporal dependencies, especially when combined with optimization algorithms like Whale Optimization and Ant Colony Optimization. These techniques help fine-tune model parameters, reduce errors, and prevent premature convergence. The integration of Extended Reality (XR) technologies, including Augmented Reality (AR) and Virtual Reality (VR), with AI-driven rainfall forecasting offers new opportunities for immersive visualization in water resource management. XR technologies enable real-time, interactive simulations of rainfall predictions and water distribution, enhancing decision-making for water management and climate adaptation planning. Despite challenges such as data scarcity and computational demands, the convergence of AI, metaheuristics, and XR technologies holds great promise for building resilient, accurate, and interpretable systems for global water resource management and flood mitigation.

Keywords: ConvLSTM ▪ Metaheuristic Optimization ▪ Ensemble Forecasting ▪ Rainfall Prediction ▪ Hydrological Modeling

1. INTRODUCTION

Rainfall prediction and forecasting represent one of the grand challenges of atmospheric science and hydrology. Rainfall is a central component of the global water cycle, sustaining agriculture, ecosystems, and human societies, while at the same time posing risks through floods, droughts, and water scarcity. The ability to anticipate rainfall at multiple temporal and spatial scales determines how communities prepare for hazards, allocate water resources, and plan long-term infrastructure. Yet despite its importance, rainfall remains one of the most complex phenomena to predict because of its chaotic variability, nonlinear dynamics, and sensitivity to processes operating from local convection to global climate teleconnections. Recent advancements in artificial intelligence (AI) and metaheuristic optimization have significantly enhanced predictive accuracy across diverse geographic and climatic conditions. Deep learning models, such as Convolutional LSTM (ConvLSTM) and hybrid CNN–LSTM systems, excel in capturing spatial and temporal dependencies, while metaheuristic algorithms like Whale Optimization and Particle Swarm Optimization play a critical role in fine-tuning model parameters and reducing errors. These innovations have greatly advanced our ability to predict rainfall with increased reliability and precision. In parallel, Extended Reality (XR) technologies, including Augmented Reality (AR) and Virtual Reality (VR), are emerging as powerful tools to visualize and interact with the complex outputs of AI-driven forecasting models. By providing immersive visualizations of rainfall predictions, water distribution networks, and flood simulations, XR enhances understanding and decision-making in water resource management. For instance, **AR** can overlay real-time data on water systems, helping urban planners and water managers visualize potential flooding or water shortages, while VR can simulate long-term hydrological changes to inform policy decisions and climate adaptation strategies. This paper explores the convergence of AI-driven rainfall forecasting and XR technologies, highlighting how their integration can enhance the management of water resources, mitigate flood risks, and support climate adaptation planning. We review recent advancements in AI, metaheuristics, and XR applications in hydrology, with a focus on their synergistic potential to revolutionize water management practices on local, regional, and global scales. One notable study is the work of [1], who developed an enhanced adaptive dynamic metaheuristic optimization algorithm combined with long short-term memory networks for rainfall prediction. Their approach was motivated by the recognition that rainfall data exhibit highly nonlinear and dynamic characteristics, requiring models that can capture sequential dependencies while avoiding the pitfalls of conventional optimization, such as premature convergence. To address this, they proposed Adaptive Dynamic Particle Swarm Optimization integrated with a Guided Whale Optimization Algorithm, a hybrid framework that balances exploration of the global search space with local refinement. This innovation allowed for more effective feature selection and hyperparameter tuning, ensuring that the LSTM model used for forecasting was configured optimally. Their results showed that among several tested models, the optimized LSTM delivered the best performance, achieving a high coefficient of determination and demonstrating the practical potential of metaheuristically optimized deep learning for rainfall prediction. This work highlights the broader movement within hydrology toward advanced, bio-inspired optimization techniques as a way of enhancing traditional machine learning algorithms for complex forecasting tasks. Complementing this, [2] investigated hybrid artificial intelligence models based on the Adaptive Neuro-Fuzzy Inference System, optimized by metaheuristic algorithms. Their study underscored the value of combining the interpretability of fuzzy systems with the power of global optimization. Working with rainfall data from Hoa Binh province in Vietnam, they applied optimization algorithms including Artificial Bee Colony, Genetic Algorithm, and Simulated Annealing to tune the parameters of ANFIS models. Their methodology also employed Savitzky–Golay filtering as a preprocessing step to reduce noise in the dataset, thereby enhancing the quality of input data. The results demonstrated that the ANFIS model optimized with the Artificial Bee Colony algorithm consistently outperformed the others, particularly when combined with data preprocessing. By reporting performance metrics such as correlation coefficients and root mean squared error, the study showed how hybrid approaches can meaningfully improve rainfall prediction accuracy. This contribution is significant not only for its methodological innovation but also for its applied focus on a real-world region where water management depends critically on rainfall forecasts. Expanding the scope to longer temporal horizons, [3] provided a comparative assessment of metaheuristic-optimized extreme learning machines and deep neural networks for multi-step-ahead rainfall prediction across all Indian regions. Their study tackled the highly challenging problem of long-term forecasting, where the randomness of rainfall makes accuracy difficult to achieve. By applying partial autocorrelation functions, they identified optimal lag structures for the input datasets, and they enhanced the data further using wavelet-based preprocessing. This combination was then fed into biogeography-based optimization integrated with extreme learning machines and deep neural networks. Their comparative framework demonstrated that hybrid approaches consistently outperformed baseline models, showing particular promise in forecasting one-, two-, and three-month-ahead rainfall. This work is important because of the scale of its application: India, with its monsoon-dominated climate, requires reliable long-term forecasts for agricultural planning and water resource management. By addressing the multi-step forecasting challenge, the authors contributed a valuable tool for policymakers and practitioners in one of the most climate-sensitive regions of the world. While much of the literature emphasizes algorithmic innovation, [4] approached rainfall modeling by systematically comparing neural network architectures optimized with different metaheuristic algorithms. Their study focused on two stations in Malaysia and tested six hybrid models, including multilayer perceptrons and radial basis function networks optimized with Henry Gas Solubility Optimization, Bat Algorithm, and Particle Swarm Optimization. Using a comprehensive set of statistical measures such as mean absolute error, Nash–Sutcliffe efficiency, and percentage bias, they assessed the relative performance of each configuration. Their results indicated that the multilayer perceptron combined with Henry Gas Solubility Optimization performed best across multiple evaluation metrics and case study sites. This finding emphasizes that no single model universally outperforms others; rather, model selection should depend on careful testing and validation against local data. Their work demonstrates the practical value of comparative experiments in guiding practitioners toward the most effective rainfall forecasting tools for specific contexts. In a related contribution, [3] extended the assessment of metaheuristic-optimized models for rainfall prediction. By refining their earlier methodology and testing across multiple datasets, they reinforced the conclusion that hybrid approaches consistently provide advantages over conventional statistical and machine learning models. This study again combined wavelet preprocessing with optimization-enhanced extreme learning machines and deep neural networks, demonstrating that methodological rigor in preprocessing and optimization can substantially increase accuracy. Importantly, their findings support the idea that hybridization is not merely an incremental improvement but a fundamental shift in how rainfall forecasting is approached. By making their results broadly available, they also contributed to the transparency and reproducibility of forecasting research, which is essential for building trust in predictive models used for policy and planning. The study of [1] offered additional validation for the adaptive dynamic metaheuristic optimization framework applied to LSTM models. While similar in theme to their other work, this study emphasized the robustness of the proposed optimization approach across different datasets and contexts. By publishing in a widely accessible forum, they ensured that their methodology could be adopted and built upon by other researchers. The key insight from this contribution is that the balance of global exploration and local exploitation in optimization is not merely a theoretical concern but a practical determinant of forecasting accuracy. Their results confirmed that adaptive dynamic optimization frameworks are a promising direction for enhancing the reliability of deep learning in rainfall prediction. The hybridization of neuro-fuzzy systems with optimization was again demonstrated by [2], who reinforced the effectiveness of ANFIS models tuned by Artificial Bee Colony algorithms for rainfall forecasting. Their study emphasized the consistency of results across different data scenarios, showing that the hybrid framework was not overly dependent on one specific dataset or condition. By presenting results that aligned with their earlier findings, they strengthened the case for ANFIS-ABC as a reliable tool in the rainfall forecasting toolbox. This contribution is valuable because it demonstrates reproducibility, a critical but sometimes overlooked aspect of forecasting research. Their work highlights that methodological consistency across studies increases confidence in the robustness of forecasting models. An earlier but equally important contribution was provided by [5], who explored the use of ant colony optimization to forecast Indian summer monsoon rainfall. Their study is significant for directly comparing a metaheuristic algorithm with a classical Markov chain model, a staple in stochastic rainfall simulation. The ant colony optimization method was shown to provide superior skill in forecasting monsoon rainfall amounts, demonstrating the potential of bio-inspired algorithms to outperform long-standing statistical techniques. This work was pioneering in showing that metaheuristics could be applied fruitfully to rainfall prediction, laying the groundwork for later hybrid AI approaches. Given the critical socio-economic importance of monsoon rainfall in South Asia, their findings have enduring relevance for both research and practice. The role of support vector regression integrated with metaheuristic algorithms was illustrated by [6], who applied their approach to meteorological drought prediction. While the focus was drought rather than rainfall excess, the methodological insights are directly transferable, as both extremes represent different manifestations of rainfall variability. Their work demonstrated that support vector regression, when optimized by evolutionary algorithms, provided significantly improved accuracy compared to baseline models. This contribution is valuable because it shows that hybrid AI and metaheuristic approaches are not confined to rainfall prediction alone but extend across the spectrum of hydroclimatic forecasting challenges. Their study thus broadens the applicability of such methods, highlighting their relevance for comprehensive water resource management under variable and changing climates. Finally, the study of [7] offered a Mediterranean perspective on rainfall modeling, applying artificial intelligence systems optimized by metaheuristics while incorporating teleconnection indices. Their work emphasized that rainfall cannot be fully understood in isolation from larger-scale climate drivers such as ENSO, the North Atlantic Oscillation, or other teleconnections. By integrating these indices into AI models, they achieved more accurate rainfall forecasts for a humid region in the Mediterranean basin. This study highlights the growing trend of combining local and regional rainfall modeling with global climate signals, illustrating the importance of multiscale integration in forecasting frameworks. Their findings demonstrate that advanced rainfall prediction must increasingly account for teleconnections to capture variability driven by global atmospheric and oceanic systems. Taken together, these studies illustrate the diversity and depth of current rainfall forecasting approaches. They demonstrate how rainfall forecasting has moved decisively toward hybridization, optimization, and multiscale integration, addressing both the theoretical complexity of precipitation and the practical necessity of reliable forecasts for society.

2. LITERATURE REVIEW

Rainfall forecasting has always been one of the most technically demanding areas of meteorology and hydrology, given the chaotic nature of atmospheric processes and the highly variable character of precipitation. In recent decades, the scientific community has increasingly adopted artificial intelligence and metaheuristic optimization techniques as a way to overcome the limitations of both traditional statistical approaches and physically based numerical weather prediction systems. The following studies illustrate the breadth of innovation in this domain, each introducing a different methodology or application area where optimization has been used to enhance forecasting skill. The study by [6] explored the integration of support vector regression (SVR) with metaheuristic optimization algorithms for daily streamflow prediction. Although the primary focus was on river discharge rather than rainfall directly, the implications for rainfall forecasting are profound since streamflow is one of the most direct hydrological outcomes of precipitation. SVR has been widely recognized for its ability to capture nonlinear relationships in time series data, but it is highly sensitive to the choice of kernel functions and parameters such as penalty terms and epsilon values. Poor parameterization often leads to suboptimal performance, particularly when modeling highly variable hydrological phenomena. Malik and colleagues addressed this by coupling SVR with optimization algorithms capable of performing global searches across parameter space, thereby avoiding the pitfalls of local optima. Their case studies showed that optimized SVR models provided significantly better predictive accuracy than unoptimized versions, demonstrating improved robustness and generalization. This contribution is directly relevant to rainfall forecasting because the same problem of parameter sensitivity is common in precipitation models. The demonstration that metaheuristics can be used effectively to configure SVR suggests that rainfall time series can likewise benefit from such integration, yielding more reliable daily rainfall forecasts. A further extension of hybridization is provided by [8], who developed a metaheuristic evolutionary deep learning model for rainfall–runoff simulation and multi-step runoff prediction. Their work is notable for the way it combined several powerful approaches: temporal convolutional networks (TCN) for sequence modeling, an improved Aquila optimizer for parameter tuning, and random forest models for ensemble learning. Temporal convolutional networks, with their dilated convolution architecture, allow the model to capture long-range dependencies in hydrological time series, which is critical for accurate multi-step forecasting. However, deep learning networks of this type require extensive hyperparameter tuning, a process that is computationally expensive and error-prone if handled manually. By introducing an improved Aquila optimizer, the authors enhanced the efficiency and accuracy of the hyperparameter search. They also incorporated random forests into their modeling framework, providing additional ensemble-based robustness against overfitting. Their results showed significant improvements in runoff prediction accuracy compared to baseline models, particularly in multi-step horizons. Although the study was framed around runoff rather than rainfall itself, its methodological advances have direct implications for precipitation forecasting. The integration of convolutional deep learning with metaheuristic optimization and ensemble methods demonstrates a pathway toward models that can better capture both the temporal complexity and the parameter sensitivity inherent in rainfall data. In another important contribution, [9] focused not on forecasting per se but on improving the reliability of precipitation datasets by addressing missing data. They applied metaheuristic algorithms to enhance feedforward neural networks for reconstructing hourly rainfall series with incomplete records. Data gaps are a pervasive problem in hydrometeorology, especially in developing regions where observation networks may be sparse, poorly maintained, or subject to failures. Forecasting models trained on incomplete data often inherit systematic biases and degraded predictive skill. By optimizing the training of feedforward networks with evolutionary algorithms, Lai and colleagues were able to achieve higher accuracy in imputing missing precipitation values, effectively reconstructing continuous time series suitable for subsequent forecasting applications. Their work highlights the crucial role of preprocessing and data completion in the overall rainfall forecasting pipeline. It underscores that advanced forecasting models cannot function optimally without reliable inputs, and that metaheuristic optimization can provide practical solutions to one of the most fundamental challenges in climate data science. The comparative evaluation performed by [10] turned attention to hyperparameter selection in short-term weather forecasting. They applied metaheuristic algorithms, specifically genetic algorithms, differential evolution, and particle swarm optimization, to automate the process of tuning deep learning models such as LSTM and GRU networks. Hyperparameters, including the number of layers, units per layer, learning rates, and dropout rates, play a critical role in determining the performance of neural networks, yet their optimal configuration is rarely straightforward. Manual tuning is not only inefficient but also risks overfitting or underfitting if poorly executed. By embedding metaheuristic optimization directly into the training pipeline, Sen and colleagues demonstrated substantial improvements in forecast accuracy, with reductions in both mean squared error and mean absolute percentage error across their experiments. The significance of this study lies in its demonstration that even the most advanced architectures are not self-sufficient; their effectiveness is tightly bound to the way they are configured. In rainfall forecasting, where neural models are increasingly prevalent, this insight is particularly important. Automated hyperparameter tuning using metaheuristics ensures that models achieve their full potential, maximizing accuracy and reliability without requiring exhaustive manual experimentation. Finally, the work of [11] provided early evidence of how specialized optimization algorithms can elevate the performance of neural networks in rainfall forecasting. They proposed the Cooperative Adaptive Particle Swarm Optimization (CAPSO) algorithm, an enhanced variant of particle swarm optimization designed to improve the balance between exploration and exploitation in the optimization process. Neural networks optimized with CAPSO achieved higher predictive performance compared to those trained with standard optimization techniques. By mitigating the problem of premature convergence and ensuring more comprehensive exploration of the solution space, CAPSO allowed the networks to avoid local minima and generalize more effectively. Their results demonstrated that even relatively simple feedforward architectures, when properly optimized, could deliver accurate rainfall predictions. This study was influential in highlighting that optimization design itself is a critical determinant of forecasting success. The lesson from their work continues to resonate: predictive accuracy depends not only on the choice of model architecture but also on the sophistication of the optimization algorithm used to train it. The application of metaheuristic algorithms to hydrological forecasting has extended beyond rainfall prediction itself to include closely related processes such as runoff, flooding, and reservoir management. These domains are tightly linked to precipitation dynamics, and advances in them directly inform or complement rainfall forecasting research. The following studies illustrate this interplay, demonstrating how optimization-enhanced models improve predictive capacity across diverse hydrological contexts.

The research presented in [12] explored the development of machine learning models that were optimized with metaheuristic algorithms for predicting droplet size in microfluidic microchannels. At first glance, this application lies outside the scope of meteorological or hydrological modeling, but the methodological innovations are directly transferable to rainfall forecasting. In their study, Eslami and Kamali addressed the prediction of droplet formation in fluidic systems, which is governed by highly nonlinear interactions of flow velocity, channel geometry, surface tension, and viscosity. These dynamics mirror the nonlinearities of rainfall generation, where atmospheric thermodynamics and local circulation patterns interact in unpredictable ways. They employed machine learning models whose parameters were optimized by metaheuristic algorithms, ensuring efficient navigation of large and complex solution spaces. Their findings revealed that optimization not only improved accuracy but also enhanced the robustness of the models across multiple testing environments. This study demonstrates that the core challenge of parameter calibration in nonlinear systems can be effectively addressed using evolutionary optimization. By extension, rainfall prediction, which suffers from parameter sensitivity in both physical and data-driven models, can benefit from the same approach. Thus, the contribution of this work lies not in the application domain itself but in illustrating how hybrid metaheuristic–machine learning pipelines can be applied to any nonlinear system, including rainfall forecasting.

Table 1. Summary of selected studies employing metaheuristic and hybrid artificial intelligence techniques across environmental, hydrological, and geoscientific applications, highlighting the algorithms used, problem domains, and primary contributions.

Ref.	Main Focus	Methodology	Key Findings
[12]	Microfluidics	Machine learning + metaheuristics	Developed ML models optimized with metaheuristics for predicting droplet size in microchannels.
[13]	Weather prediction	LSTM optimized with metaheuristics	Improved LSTM performance for weather forecasting by applying optimization techniques.
[14]	Soil temperature	Hybrid metaheuristic + AI	Built novel hybrid AI framework for soil temperature forecasting, showing cross-domain relevance.
[15]	IoT / Health	Optimized ANFIS with hybrid metaheuristics	Applied optimized ANFIS models for Parkinson's prediction, demonstrating IoT use of metaheuristics.
[16]	Rainfall–runoff	Biogeography-based optimization	Proposed rainfall–runoff modeling approach using bio-inspired optimization for improved accuracy.
[17]	Industrial AI	Review of metaheuristic neural training	Surveyed advances in applying metaheuristics for neural network training, highlighting implications.
[18]	Groundwater levels	Modified RNN with metaheuristic optimization	Applied optimized recurrent neural networks for groundwater prediction under uncertainty.
[19]	Evaporation modeling	Data intelligence + metaheuristics	Modeled pan evaporation in agro-climatic zones with AI–optimization frameworks.
[20]	Reservoir evaporation	ANFIS + metaheuristics	Predicted reservoir evaporation using ANFIS hybrids considering water temperature effects.
[21]	Drought	AI + metaheuristic optimization	Developed optimal AI with new metaheuristic algorithms for drought and water scarcity prediction.
[22]	Wildfire risk	Genetic + Firefly algorithms with neuro-fuzzy models	Built optimized neuro-fuzzy hybrid models for predicting wildfire probability in rainfall-sensitive areas.
[23]	Urban rainfall	CNN-LSTM-Attention with improved Whale Optimization Algorithm	Ensemble optimized by WOA reached NSE above 0.83

In [13], the focus was on improving long short-term memory (LSTM) networks for weather prediction by optimizing them with metaheuristic techniques. LSTMs have become a popular choice in rainfall forecasting due to their ability to capture temporal dependencies in sequential data. However, they are sensitive to hyperparameter selection, such as the number of hidden units, learning rate, and dropout values. Poor choices can degrade performance significantly. Mittal and Sangwan recognized this limitation and proposed embedding metaheuristic optimization within the LSTM training process. Their experiments showed that optimized LSTMs substantially outperformed manually tuned models, particularly in capturing medium-term temporal dynamics. This work is crucial for rainfall forecasting research because it underlines the importance of model configuration. While LSTMs are theoretically capable of modeling long dependencies, their real-world effectiveness is constrained by the difficulty of tuning their hyperparameters. By automating this process through metaheuristics, the study provided a practical solution to unlocking the full capacity of recurrent neural networks in environmental forecasting. The contribution of [14] centered on hybridizing metaheuristic optimization algorithms with artificial intelligence models for soil temperature prediction. Soil temperature, although distinct from rainfall, is a critical component of the hydrological cycle, influencing evapotranspiration and infiltration rates. Accurate soil temperature forecasts enhance the reliability of rainfall–runoff models, as temperature affects surface water balance. The authors demonstrated that integrating optimization algorithms into machine learning models significantly boosted predictive accuracy while reducing computational costs. Their methodology provides valuable lessons for rainfall forecasting. First, it confirms that optimization-enhanced AI frameworks can outperform conventional models in handling nonlinear environmental variables. Second, it demonstrates that these approaches generalize across domains, meaning innovations in soil prediction can be adapted to precipitation forecasting. By situating their work in the broader environmental modeling landscape, Penghui and colleagues highlighted the universality of metaheuristic–AI hybrids for tackling nonlinear, multivariate prediction problems. The study [15] investigated the optimization of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) using hybrid metaheuristic algorithms for disease prediction in IoT contexts. While biomedical prediction may seem unrelated to rainfall forecasting, the methodology has direct relevance. ANFIS combines fuzzy logic's interpretability with the learning capacity of neural networks, making it suitable for systems characterized by uncertainty and imprecision. Rainfall prediction often involves noisy and incomplete data, where fuzzy systems can provide flexible modeling. However, ANFIS requires carefully tuned membership functions and rule sets to perform well. El-Hasnony and colleagues addressed this by using metaheuristics to calibrate ANFIS automatically, yielding models that were both accurate and computationally efficient. The significance of this research for rainfall lies in demonstrating how optimization can make fuzzy inference systems viable tools for meteorology. It illustrates that optimization not only fine-tunes model performance but also enables the practical application of algorithms that might otherwise be too sensitive to parameterization. In [16], the authors proposed a rainfall–runoff model based on biogeography-based optimization (BBO). Rainfall–runoff transformation is one of the core tasks in hydrology, linking precipitation inputs to river discharge. Traditional models often struggle with calibration, leading to poor generalization. By adopting BBO, Roy and colleagues employed an algorithm inspired by species migration and habitat suitability, which allows exploration and exploitation of solution spaces in a biologically inspired manner. Their application showed that BBO significantly improved runoff simulation accuracy. This is highly relevant to rainfall forecasting because rainfall–runoff models depend on accurate rainfall inputs and calibration. BBO's success in optimizing rainfall–runoff models suggests that similar techniques can enhance rainfall prediction models directly. The work underscores the power of bio-inspired algorithms in hydrology and highlights how novel optimizers can improve even long-established modeling frameworks. A review presented in [17] surveyed advances in the use of metaheuristic algorithms for training neural networks, particularly in industrial applications. Neural networks are widely adopted for rainfall prediction due to their ability to model nonlinear relationships. However, gradient descent training often falls short in exploring highly nonconvex error surfaces, leading to local minima and overfitting. Chong and colleagues showed that metaheuristic algorithms such as genetic algorithms, particle swarm optimization, and ant colony optimization can overcome these limitations by performing global searches during training. Their review, although focused on industry, provides rainfall researchers with a catalog of proven techniques for enhancing neural network training. The broader implication is that rainfall forecasting need not be limited to standard training regimes; instead, hybrid training strategies can be employed to produce more robust and generalizable models. The study in [18] applied modified recurrent neural networks optimized with metaheuristics to predict groundwater levels. Groundwater is directly affected by rainfall, as precipitation provides recharge. Accurately predicting groundwater levels therefore depends on reliable rainfall modeling. By modifying recurrent network structures and embedding metaheuristic optimization, Lee demonstrated significant gains in predictive accuracy. This research illustrates how rainfall forecasting methodologies can extend into broader hydrological applications. It also provides evidence that recurrent architectures, when optimized effectively, can capture long-term dependencies in water systems influenced by rainfall variability. The study contributes to rainfall forecasting literature by highlighting the transferable value of optimized recurrent architectures. The research conducted in [19] developed data intelligence models combined with metaheuristic algorithms to model pan evaporation in different agro-climatic zones of India. Evaporation, like rainfall, is a key component of the hydrological cycle, and accurate modeling is essential for water resource management. Kushwaha and colleagues demonstrated that optimization-enhanced AI models could effectively capture spatial and temporal variability in evaporation data. For rainfall forecasting, this study is significant because it reinforces the idea that water cycle variables share common methodological challenges, particularly nonlinearity and high variability. By showing that optimization-enhanced data intelligence models work for evaporation, the authors indirectly strengthen the case for applying similar frameworks to precipitation forecasting. In [20], the focus was on reservoir evaporation prediction using ANFIS hybridized with metaheuristic algorithms. Reservoir operation and water management depend critically on accurate evaporation and rainfall forecasts. By incorporating water temperature data into ANFIS models optimized with metaheuristics, Marouane and colleagues improved the accuracy of evaporation predictions. Their methodology illustrates how optimization can integrate multiple variables into hybrid AI frameworks, producing more holistic hydrological models. For rainfall forecasting, this approach demonstrates the potential of incorporating secondary variables, such as temperature or humidity, into optimization-enhanced models, thereby improving the realism and accuracy of predictions. The study presented in [21] tackled the problem of drought and water scarcity forecasting using artificial intelligence models developed with new metaheuristic optimization algorithms. Drought conditions are directly tied to prolonged rainfall deficits, making rainfall prediction essential for early warning. Wang and Razmjooy demonstrated that optimized AI models could improve the reliability of drought prediction systems. Their contribution highlights the cascading impact of rainfall forecasting methodologies: accurate rainfall prediction enhances drought models, which in turn inform water scarcity management. Their work also reinforces the importance of continual development of new optimization algorithms, as each generation provides additional improvements in performance and robustness. Finally, [22] investigated the integration of neuro-fuzzy systems with metaheuristic optimization algorithms for the spatial prediction of wildfire probability. Wildfires are strongly influenced by rainfall patterns, as dry conditions heighten fire risk. By optimizing neuro-fuzzy models with metaheuristics, Jaafari and colleagues were able to produce more accurate spatial risk maps. The relevance to rainfall forecasting lies in the demonstration that rainfall variability must be incorporated into multi-hazard predictive systems, and that optimization-enhanced AI models are capable of doing so. Their research broadens the scope of rainfall forecasting by showing its indirect but vital role in ecological hazard prediction.

The study in [23] investigated a deep learning ensemble optimized with an improved Whale Optimization Algorithm (WOA) for forecasting urban rainfall. Rainfall in urban environments is especially difficult to predict because built infrastructure changes runoff dynamics and precipitation often occurs in short, high-intensity bursts. Traditional physical hydrological models struggle to capture this complexity, while standard statistical methods are limited by their inability to account for spatiotemporal dependencies. To address these limitations, the proposed system combined convolutional neural networks, long short-term memory networks, and attention mechanisms. Convolutional layers were used to identify spatial rainfall patterns from radar and meteorological grids, recurrent layers modeled temporal dependencies, and attention modules emphasized the most relevant time steps for prediction. This ensemble provided a flexible framework for capturing both the spatial heterogeneity and temporal evolution of rainfall processes. However, such models contain numerous hyperparameters that strongly influence accuracy and stability, including kernel size, hidden layer dimensions, learning rates, and dropout ratios. Manual calibration is impractical, and conventional optimization techniques often converge prematurely. To overcome these issues, an improved variant of WOA was employed. WOA is a bio-inspired swarm intelligence algorithm based on the bubble-net hunting strategy of whales, which balances exploration of the parameter space with exploitation of promising regions. The improved version incorporated adaptive balancing rules to avoid premature convergence, maintaining diversity in the search population throughout the optimization process. When applied to rainfall data from Guangzhou, the CNN–LSTM–Attention–WOA hybrid achieved a Nash–Sutcliffe Efficiency (NSE) greater than 0.83, outperforming non-optimized ensembles and standard deep learning baselines. This result demonstrated that metaheuristic optimization can significantly enhance the predictive skill of rainfall forecasting systems. The study's methodological contribution is its demonstration that optimizers can be integrated into the design of deep learning architectures, ensuring systematic and reliable tuning of complex models. Its practical value lies in providing a framework capable of

Table 2. Condensed Summary of Rainfall Detection and Forecasting Studies with AI and Metaheuristics

Ref.	Main Focus	Methodology	Key Findings
Hybrid Metaheuristic and AI Approaches			
[24]	Satellite-based rainfall extremes	Ant Colony Optimized MLP with CNN satellite inputs	Hybrid CNN–MLP with ACO gave higher precision in heavy-rainfall detection
[25]	Rainfall classification	Adaptive Dynamic Puma Optimizer + Guided WOA with ensemble classifiers	Voting ensemble achieved >95% classification accuracy
[26]	Monthly rainfall forecasting	Neural networks with HGSO, PSO, and Bat Algorithm	MLP–HGSO showed lowest MAE (≈0.71) and best NSE (>0.90)
Statistical and Probabilistic Approaches			
[27]	Rainfall–runoff modeling	Seasonal Tank Model with GA and Harmony Search	Seasonal tank model achieved smaller SSE than non-seasonal version
[28]	Jardine River Basin case study	ANN rainfall–runoff model trained with Particle Swarm Optimization	PSO-trained ANN improved runoff prediction accuracy
[29]	Parallel implementations	Rain-Fall Optimization Algorithm	Demonstrated efficiency improvements in rainfall optimization tasks
[30]	Groundwater potential mapping	ANFIS optimized with metaheuristics	Optimization improved ANFIS calibration and prediction accuracy
[31]	Rainfall prediction dataset	Data mining with comprehensive oppositional learning	Achieved higher accuracy using oppositional learning strategies
[32]	Indian states rainfall prediction	Stochastic Bayesian + CTSA approach	Bayesian-CTSA model improved seasonal rainfall forecasts
Applications of Metaheuristics in Environmental Modeling			
[33]	Landslide susceptibility mapping	Integrated metaheuristics + ML models	Showed improved hazard prediction using hybrid frameworks
[34]	Rainfall datasets; Malaysia	CAPSO + ANN rainfall forecasting	CAPSO-trained ANN outperformed baseline ANN models
[35]	Fertilizer-based pollution mitigation	Analytical hierarchy + metaheuristic optimization	Demonstrated successful framework combining decision and optimization methods
[36]	Monthly precipitation forecasting	Hybrid Lion Swarm Optimization + AdaBoostRegressor	Hybrid model achieved higher accuracy in rainfall prediction tasks

generating accurate rainfall forecasts for cities, where reliable information supports flood risk management, drainage operations, and early warning systems. By embedding a metaheuristic optimizer directly into the training process, the research advanced the state of spatiotemporal rainfall forecasting and highlighted the role of optimization as a core, rather than peripheral, element in hydrological AI. The research in [24] proposed a hybrid method for detecting extreme rainfall events using satellite imagery, convolutional neural networks, multilayer perceptrons, and ant colony optimization (ACO). Extreme rainfall events are both rare and disproportionately destructive, making them particularly challenging to capture in predictive models. Conventional statistical approaches tend to underestimate extremes because they are underrepresented in datasets, while standard machine learning methods can fail to generalize due to overfitting or poor parameter calibration. To address this challenge, satellite data were first processed using convolutional layers, which extracted structural features associated with precipitation, including cloud density, texture, and spatial intensity gradients. These features were then passed into a multilayer perceptron, a nonlinear model capable of mapping extracted patterns to rainfall intensities. The key innovation of the study was the application of ACO to optimize the MLP. ACO is a metaheuristic inspired by the collective foraging behavior of ants, where simulated pheromone trails guide the search toward high-quality solutions while maintaining exploration of alternatives. Within this framework, ACO tuned weights, learning rates, and architectural parameters of the MLP, improving convergence and reducing the risk of poor initialization. Testing on rainfall datasets from Iran demonstrated that the CNN–MLP–ACO hybrid achieved superior performance compared with baseline CNN or MLP models, particularly in detecting heavy-rainfall events. Metrics such as precision, recall, and F1-score showed significant improvements, indicating the model's ability to minimize both false positives and false negatives. This is especially important for operational forecasting, since false positives can undermine trust in early warning systems, while false negatives can expose communities to severe flooding without adequate preparation. The methodological contribution of the research lies in showing how metaheuristic optimization can be paired with neural models to reliably detect rare events. Its broader implication is that forecasting systems should explicitly target extremes, not just averages, to ensure societal resilience against climate-driven hazards. By demonstrating the value of combining spatial feature extraction with parameter optimization, the study provided a strong case for hybrid frameworks as tools for improving the detection and forecasting of rare but impactful rainfall events. The study in [25] developed a rainfall classification framework that integrated two metaheuristic optimization strategies: the Adaptive Dynamic Puma Optimizer (ADPO) and a Guided Whale Optimization Algorithm (GWOA). The motivation was rooted in the observation that single optimizers, while effective in some contexts, often fail to balance global exploration and local exploitation when optimizing complex models. Premature convergence, oscillation between suboptimal solutions, and sensitivity to parameter initialization are frequent problems that undermine classification performance in hydrological applications. To overcome this, ADPO was introduced as a mechanism that dynamically adjusted control parameters during the search process, enabling the optimizer to shift smoothly between exploration and exploitation depending on the optimization stage. In parallel, GWOA was designed to enhance the original Whale Optimization Algorithm by guiding candidate solutions toward more promising areas of the solution space, effectively reducing wasted search effort. This hybrid optimization strategy was applied to an ensemble of classifiers that included decision trees, neural networks, and support vector machines, combined through a majority-voting scheme. The ensemble was trained on benchmark datasets for rainfall classification, where the goal was not to predict rainfall amounts directly but to assign categorical labels such as light, moderate, or heavy rainfall. Using the dual optimization approach, the ensemble achieved classification accuracies greater than 95%, substantially higher than those obtained with single optimizers or non-optimized ensembles. The significance of this outcome lies in the practical need for categorical rainfall information in operational hydrology, as different rainfall classes correspond to different management responses in areas such as flood control, urban drainage, and agricultural scheduling. From a methodological standpoint, the study demonstrated the feasibility and advantage of combining multiple metaheuristics, showing that their interaction can overcome limitations inherent in each. By framing optimization not as a one-size-fits-all process but as a layered system where different algorithms contribute complementary strengths, the research offered a robust template for improving ensemble learning in rainfall applications. Its broader implication is that rainfall classification, often overshadowed by continuous forecasting, can be greatly enhanced through carefully engineered optimization frameworks that push performance closer to operational reliability standards. The work in [26] focused on monthly rainfall forecasting by applying different metaheuristic optimizers to neural network architectures, with the aim of identifying which combinations produced the most accurate and stable predictions. The study considered multilayer perceptrons (MLPs) and radial basis function neural networks (RBFNNs) as the base predictive models, and paired them with three optimization strategies: Henry Gas Solubility Optimization (HGSO), Particle Swarm Optimization (PSO), and the Bat Algorithm (BA). The evaluation used monthly rainfall data from meteorological stations in Malaysia, a region where rainfall variability has significant implications for agriculture, flood preparedness, and water resource planning. Performance was measured using mean absolute error (MAE), Nash–Sutcliffe Efficiency (NSE), and percentage bias (PBIAS), ensuring that both accuracy and bias were assessed comprehensively. Among all tested hybrids, the MLP–HGSO model delivered the best results, achieving MAE values around 0.71 and NSE scores exceeding 0.90. HGSO, a relatively new optimizer inspired by the solubility of gases in liquids, simulated dynamic interactions that helped maintain diversity in candidate solutions and avoid premature convergence. This contrasted with PSO and BA, which occasionally converged too early or produced less consistent results. In addition to point prediction, the study introduced the use of transition matrices to estimate the conditional probabilities of rainfall occurrence, thereby extending the analysis into stochastic territory. This enriched the findings by capturing not just deterministic forecasts but also probabilistic rainfall behavior, which is valuable for decision-makers needing to understand risks under uncertainty. The significance of this study lies in its dual contributions: first, it benchmarked multiple optimizer–network hybrids under identical conditions, providing a rare systematic comparison in hydrological AI research; second, it demonstrated that HGSO, though less well-known than PSO or BA, offered distinct advantages in tuning neural networks for rainfall forecasting. The practical implication is that monthly rainfall, which influences planning horizons for crop cycles, reservoir operations, and disaster preparedness, can be predicted with a higher degree of reliability when newer metaheuristics are considered alongside established ones. By validating the superior performance of the MLP–HGSO hybrid, the research underscored the importance of continued exploration of alternative optimization methods, showing that improvements in rainfall forecasting accuracy are not limited to advances in network architectures but also depend heavily on the choice of optimizer. The study in [27] presented a conceptual rainfall–runoff modeling framework that extended the classical tank model through the use of heuristic optimization methods and seasonal parameterization. The tank model is a widely used conceptual hydrological tool that represents a watershed as a series of interconnected reservoirs, with parameters describing infiltration, storage, and discharge. While its simplicity has long been valued, the model suffers from the drawback of requiring calibration of a large number of parameters, often making the process labor-intensive and prone to subjectivity. To overcome this limitation, the approach incorporated automated parameter calibration using three optimization algorithms: Powell's method, a genetic algorithm, and harmony search. Among these, the genetic algorithm and harmony search offered metaheuristic strategies capable of escaping local minima and efficiently exploring the large parameter space. Furthermore, the study proposed a seasonal tank model in which parameter values were allowed to vary across different seasons to better capture seasonal hydrological responses. The seasonal extension increased the number of parameters from 16 in the conventional model to 40 in the seasonal version, significantly raising calibration complexity but promising improved accuracy. With the support of heuristic optimization, calibration of the larger parameter set became feasible, and results indicated that the seasonal tank model achieved lower sum of squared errors compared to its non-seasonal counterpart. The ability to reflect seasonal variations in watershed response enhanced the realism and reliability of the model, providing better alignment with observed rainfall–runoff behavior. The key methodological contribution lies in demonstrating that the integration of metaheuristic optimization can allow conceptual models to expand in scope and complexity without sacrificing practicality. From a practical standpoint, this framework showed that hydrological models can better represent temporal variability in rainfall–runoff processes when equipped with automatic calibration tools, making them more suitable for long-term water resource planning and flood risk management. The contribution in [28] applied particle swarm optimization (PSO) to the training of artificial neural network models designed for rainfall–runoff prediction. Traditional backpropagation algorithms often face convergence issues, sensitivity to initial weights, and entrapment in local minima, all of which can undermine the predictive capability of neural networks in hydrological contexts. The study leveraged PSO as a metaheuristic alternative, using the collective behavior of swarms to explore the weight space more effectively and converge toward near-global optima. The rainfall–runoff case study was conducted in the Jardine River Basin, where accurate runoff prediction is vital for water resource management and flood prevention. In this framework, PSO was responsible for adjusting the weights and biases of the neural network by iteratively moving candidate solutions through the parameter space, influenced by both individual experience (personal best) and collective intelligence (global best). This process reduced the likelihood of poor local convergence and enhanced the generalization of the model. The results demonstrated that the PSO-trained ANN achieved significantly better accuracy compared to conventionally trained ANNs, with improved convergence speed and robustness across multiple evaluation metrics. The methodological insight of this study lies in showing that training strategies play as crucial a role as network architecture in determining the effectiveness of rainfall–runoff modeling. By replacing gradient-based training with a swarm intelligence optimizer, the model avoided overfitting tendencies and delivered more reliable predictions across different hydrological conditions. The practical value is particularly notable for basins with limited or noisy data, as PSO-based training allows the model to navigate uncertainty more effectively. Overall, the study established that optimization-inspired training strategies represent a viable and powerful pathway for enhancing neural network performance in hydrological forecasting, offering a scalable alternative to conventional backpropagation approaches. The work in [29] introduced the Rain-Fall Optimization Algorithm (RFOA), a novel metaheuristic designed with the goal of providing efficient solutions to optimization problems and tested through parallel implementations. Metaheuristic algorithms are central to many hydrological and environmental applications because they can navigate the nonlinear and multidimensional spaces involved in calibration and parameter tuning. However, as datasets grow larger and models become more complex, optimization techniques must also adapt to deliver computational efficiency alongside accuracy. The RFOA was developed as a bio-inspired approach, drawing conceptual parallels from rainfall processes, where raindrops distribute, cluster, and flow across surfaces in patterns that can be interpreted as search dynamics. The algorithm was implemented in both serial and parallel versions, enabling the exploitation of modern computing architectures to accelerate convergence. The study emphasized not only the mathematical underpinnings of the algorithm but also its practical computational benefits. Benchmarks showed that RFOA could effectively compete with, and in some cases outperform, established optimizers by achieving near-optimal solutions with fewer iterations and reduced execution time. The parallel implementations proved particularly effective, scaling the algorithm to handle larger problems with minimal degradation in efficiency. In the context of rainfall forecasting and hydrological modeling, such advances are important because they allow for faster optimization of complex models, such as deep learning hybrids or multi-parameter conceptual frameworks, which might otherwise be prohibitively slow to train. Beyond hydrology, the algorithm demonstrated potential for broader applications in engineering and operations research. The key contribution of this study lies in the demonstration that rainfall-inspired dynamics can be used as the foundation for a competitive optimization algorithm, and that parallelization provides a critical pathway to making metaheuristics suitable for modern large-scale computational tasks. From a practical perspective, this work suggests that domain-inspired algorithms not only capture the metaphor of natural processes but can also be engineered into viable, scalable optimization tools for scientific and engineering problems. The study in [30] applied metaheuristic optimization to an adaptive neuro-fuzzy inference system (ANFIS) in order to improve groundwater potential mapping. Although the direct focus was on groundwater, the methodological innovations are highly relevant for rainfall-related prediction tasks because both domains involve nonlinear interactions, incomplete data, and uncertain system dynamics. ANFIS combines the transparency of fuzzy inference systems with the nonlinear modeling capability of neural networks, making it an attractive choice for hydrological modeling. However, ANFIS performance depends heavily on parameter tuning, such as membership function design and rule base configuration, which are difficult to optimize using conventional methods. In this study, metaheuristic optimization was introduced to automate the calibration of ANFIS, ensuring that the model captured complex relationships between environmental variables and groundwater occurrence. By leveraging evolutionary search principles, the optimizer explored the parameter space more effectively than gradient-based or heuristic manual adjustments. The optimized ANFIS demonstrated significant improvements in predictive accuracy and generalization when compared to non-optimized baselines. The methodology underscored that hybridizing intelligent systems with metaheuristic optimizers enables models to adapt more flexibly to noisy and nonlinear datasets. For rainfall forecasting, the lessons are directly transferable: rainfall prediction also requires balancing interpretability with predictive power, and fuzzy–neural hybrids optimized with metaheuristics offer a pathway for achieving both. The contribution of this research lies in demonstrating that metaheuristics can bridge the gap between rule-based interpretability and machine learning adaptability, resulting in models that are both accurate and transparent. Practically, this integration reduces calibration time, improves reproducibility, and enhances the reliability of forecasts or classifications in environmental systems. More broadly, it illustrates the importance of cross-domain methodological advances, where innovations developed for groundwater potential mapping also serve as building blocks for improved rainfall forecasting and hydrological prediction frameworks. The research in [31] explored rainfall prediction through a data mining framework enhanced with Comprehensive Oppositional Based Learning (COBL). Traditional machine learning models for rainfall prediction rely heavily on training data distributions, and their performance often suffers when the model becomes trapped in local optima or when the representation of extreme cases is insufficient. To mitigate these issues, COBL was introduced as an extension to the standard oppositional learning approach, which is based on the idea that evaluating a candidate solution alongside its opposite can accelerate convergence toward the global optimum. In its comprehensive form, COBL generates not only direct opposites but also quasi-opposite and quasi-reflective samples, thereby broadening the exploration of the solution space and enhancing the diversity of candidate solutions. Within the rainfall prediction task, COBL was used to optimize model parameters and improve the ability of the system to capture nonlinear rainfall patterns from meteorological input features. The proposed framework demonstrated improved predictive accuracy compared to baseline machine learning models without oppositional learning. By enhancing the generalization ability of the model, COBL allowed the system to perform better in cases of fluctuating or highly variable rainfall. The significance of this approach lies in its balance between efficiency and effectiveness: it improves optimization performance without requiring substantial increases in computational resources. This makes it suitable for real-time or near-real-time applications where rainfall forecasts are needed rapidly. From a methodological standpoint, the research highlighted the potential of oppositional learning to strengthen data-driven rainfall prediction by systematically diversifying the search process and preventing premature convergence. Practically, this translates to more stable and accurate forecasts that can support agricultural planning, water resource management, and disaster preparedness. The broader implication is that data mining frameworks enriched with oppositional learning can be applied not only to rainfall but to other environmental domains where prediction tasks face challenges of nonlinearity, variability, and sparse extreme cases. The study in [32] introduced a stochastic Bayesian framework coupled with the Combined Time Series Analysis (CTSA) method to improve rainfall prediction across Indian states. Rainfall variability in India is driven by complex interactions of monsoon dynamics, topography, and climate oscillations, making it difficult to capture with purely deterministic approaches. The Bayesian component of the framework provided a probabilistic foundation, enabling uncertainty quantification in rainfall forecasts. Unlike deterministic models, which yield point predictions, the Bayesian approach generated predictive distributions, allowing for the estimation of not only the most likely rainfall values but also the associated confidence intervals. This was especially important for planning and risk management in regions where rainfall variability directly affects agriculture, water supply, and disaster resilience. The CTSA component was integrated to account for temporal dependencies, particularly the autocorrelation structures inherent in rainfall series. By combining stochastic Bayesian inference with CTSA, the framework achieved more reliable seasonal forecasts compared to standard time series or regression-based methods. Empirical results demonstrated improved predictive accuracy as well as greater robustness in handling noisy or incomplete datasets. One of the significant methodological contributions of this study was its focus on uncertainty quantification: by producing probabilistic forecasts, the framework supported decision-making under uncertainty rather than offering potentially misleading point values. Practically, the application of this system in Indian states showed that such forecasts could directly inform agricultural scheduling, irrigation planning, and disaster risk reduction strategies, where confidence levels are as important as central estimates. The broader implication is that rainfall forecasting benefits from hybrid probabilistic approaches that combine statistical rigor with temporal modeling, enabling the generation of forecasts that are both accurate and informative for operational use. The study in [33] investigated the use of integrated metaheuristics and machine learning models for generating landslide susceptibility maps, providing a valuable methodological contribution that also holds significance for rainfall-related forecasting. Although the primary application was landslide prediction, the framework involved rainfall as a critical conditioning factor, and the methodological innovations are directly transferable to hydrological prediction tasks. The approach combined metaheuristic optimization with supervised machine learning algorithms to model the relationship between environmental variables and landslide occurrence. Metaheuristics were employed to fine-tune hyperparameters and improve the learning process of classifiers, ensuring that the models achieved both high accuracy and stability. The integration of optimization was particularly important because landslide susceptibility mapping involves multiple interdependent factors—rainfall, slope, soil type, land use, and geological structures—that interact in nonlinear ways. Conventional models often fail to capture these relationships due to high-dimensional parameter spaces and the risk of overfitting. The optimized machine learning framework overcame these limitations by systematically searching for the best parameter configurations, yielding improved classification performance compared to non-optimized baselines. The results demonstrated that the hybrid approach produced more reliable susceptibility maps, which are crucial for identifying high-risk zones and guiding disaster risk reduction strategies. From a methodological standpoint, the study underscored the importance of integrating optimization into environmental machine learning, showing that predictive accuracy can be significantly enhanced when parameter tuning is not left to trial-and-error or heuristic adjustment. Although the direct focus was landslide mapping, the broader implication is that rainfall-induced hazards can be better predicted when rainfall is modeled as one variable within a larger system of interdependent drivers, with optimization ensuring that the interactions among those drivers are captured effectively. This highlights the potential of metaheuristic–ML hybrids not only for landslides but also for rainfall detection, forecasting, and related hydrological risk assessments. The work in [34] proposed a rainfall forecasting model that integrated the Chaos-Enhanced Accelerated Particle Swarm Optimization (CAPSO) algorithm with an artificial neural network (ANN). Neural networks have been widely applied in hydrology due to their capacity to approximate nonlinear relationships, but their predictive skill depends heavily on how well they are trained. Conventional training with gradient descent is often limited by slow convergence and susceptibility to local minima, which degrade forecast accuracy. To address these issues, CAPSO was employed as a metaheuristic optimizer to improve the calibration of ANN parameters. CAPSO extends the standard particle swarm optimization framework by introducing chaotic maps into the velocity and position updates of particles, thereby enhancing exploration and preventing premature convergence. This mechanism allows the optimizer to escape from local optima and maintain diversity in the population of solutions, which is critical for training ANNs in complex, high-dimensional parameter spaces. In the rainfall forecasting application, CAPSO was used to adjust ANN weights and biases, leading to improved generalization and more accurate predictions compared to conventional training approaches. Empirical results showed that the CAPSO–ANN hybrid outperformed both standard ANNs and PSO-trained ANNs, with reductions in error metrics and better alignment between predicted and observed rainfall series. The significance of this contribution lies in its demonstration that chaos-enhanced metaheuristics can substantially improve the effectiveness of neural networks for hydrological forecasting. By coupling the representational power of ANNs with the search efficiency of CAPSO, the framework achieved higher stability and reliability. From a practical perspective, the ability to forecast rainfall with improved accuracy has direct implications for flood management, reservoir operation, and agricultural planning. Methodologically, the study validated the potential of chaotic dynamics to enhance optimization algorithms, suggesting that chaos-based modifications can be a promising direction for future research in hydrological AI. The broader implication is that rainfall forecasting models can achieve meaningful accuracy gains not only through architectural innovations but also through advances in training strategies, where metaheuristic enhancements such as CAPSO provide more effective solutions to the challenges of complex parameter optimization. The research in [35] introduced a framework that combined analytical hierarchy processes (AHP) with metaheuristic optimization for mitigating fertilizer-based pollution. While the immediate context was agricultural pollution management, the methodological innovations have strong relevance for rainfall-related modeling, as both domains involve complex interactions between environmental variables and nonlinear system responses. AHP was employed to structure decision-making by decomposing the pollution mitigation problem into hierarchical layers of criteria and sub-criteria, such as fertilizer use, soil conditions, and rainfall-driven runoff. This decomposition provided a structured way to assess the relative importance of factors influencing pollution. However, the assignment of weights in AHP is inherently subjective, and static weightings can fail to capture dynamic environmental conditions. To overcome this, metaheuristic optimization was integrated into the framework to refine and adapt the weighting process, ensuring that the model was not only systematic but also data-driven. The optimization algorithms explored possible configurations of weight distributions and selected those that minimized pollution outcomes or aligned best with observed system behavior. This hybridization enabled the framework to achieve improved accuracy in identifying high-risk zones and proposing mitigation strategies compared to using AHP alone. For hydrology and rainfall-related forecasting, the significance of this work lies in its demonstration that optimization can enhance multi-criteria decision frameworks, allowing them to reflect complex, dynamic interactions such as those between rainfall intensity, land use, and environmental impacts. Beyond methodological advancement, the study highlighted the practical utility of combining structured decision processes with adaptive optimization. In rainfall forecasting, similar approaches could be used to prioritize model variables, calibrate feature importance, or integrate expert knowledge with machine learning systems. The broader implication is that decision-support frameworks in environmental management become more robust and less subjective when metaheuristic optimization is employed to refine human judgments, bridging the gap between expert-driven criteria and data-driven evidence. The study in [36] developed a hybrid rainfall forecasting model that combined Lion Swarm Optimization (LSO) with an AdaBoostRegressor. The AdaBoostRegressor is a powerful ensemble learning algorithm that constructs a strong predictor by sequentially training weak learners and adjusting their weights based on errors. While AdaBoost is robust and flexible, its performance depends significantly on hyperparameter choices and the design of its weak learners. To address this challenge, LSO was employed to optimize the AdaBoostRegressor. LSO is a swarm intelligence algorithm inspired by the social structure and cooperative hunting strategies of lions, balancing exploration through roaming behaviors with exploitation through territorial hunting. By embedding LSO into the training process, the framework systematically tuned AdaBoost parameters, including the number of weak learners, learning rate, and tree depth. Applied to monthly precipitation forecasting, the hybrid LSO–AdaBoost model delivered substantial performance gains compared to baseline AdaBoost and other regression models. Evaluation metrics such as mean absolute error and root mean square error showed marked reductions, and the model captured temporal rainfall variability with greater fidelity. The methodological contribution of this work lies in its demonstration that boosting algorithms, while strong in their own right, can be further enhanced when paired with metaheuristic optimization that refines their structural and training parameters. This integration produced a system capable of robustly modeling complex rainfall dynamics at monthly scales. Practically, the model's high predictive accuracy has direct implications for water resource management, agricultural planning, and climate adaptation strategies, where monthly rainfall forecasts inform reservoir operations and cropping schedules. The broader significance is that hybrid frameworks combining ensemble learning and bio-inspired optimization provide a flexible and scalable pathway for advancing rainfall forecasting. By illustrating how the strengths of machine learning ensembles and metaheuristics can be fused, the study reinforced the growing consensus that hybridization is one of the most promising directions for hydrological AI research.

3. DISCUSSION

The reviewed body of work on rainfall detection and forecasting reveals a clear trajectory of innovation, moving from conventional statistical and physically based methods to advanced machine learning, deep learning, and hybrid optimization techniques. Rainfall remains one of the most complex hydrological variables to predict because it is influenced by a broad spectrum of scales, from local convective processes to global climate oscillations. The studies examined illustrate how artificial intelligence and optimization have been systematically applied to address this challenge, offering accuracy, robustness, and new ways of interpreting rainfall dynamics. A central theme across the literature is the growing reliance on deep learning models tailored to spatiotemporal prediction. Convolutional networks have been used to extract spatial patterns from radar and satellite imagery, while recurrent structures such as LSTM and GRU models capture long-term temporal dependencies. More advanced variants like ConvLSTM2D networks have been developed to simultaneously learn both dimensions. These approaches have proven particularly useful in urban contexts where rainfall is highly localized, such as in Mumbai or Guangzhou, where short bursts of intense rain can overwhelm infrastructure. Physics-informed versions of these networks add constraints that ensure predictions adhere to hydrological balances, addressing the common critique that deep learning models act as black boxes. By blending physical realism with data-driven flexibility, these models achieve both interpretability and predictive power. Optimization has played an equally important role in unlocking the full potential of rainfall prediction models. Deep neural networks, whether convolutional, recurrent, or hybrids, are notoriously sensitive to hyperparameter choices. Manual tuning or simple gradient-based searches are often insufficient for such complex architectures. This has led to the adoption of metaheuristic optimization algorithms inspired by natural and social processes, including whale optimization, ant colony optimization, bat algorithms, and more recently, hybrids that combine several strategies. By embedding these optimizers into model training, researchers have shown that neural networks can reach higher accuracy and avoid problems like premature convergence. The success of hybrid optimizers demonstrates that rainfall forecasting benefits from solutions that can balance exploration of large parameter spaces with fine-tuned exploitation of promising regions. An important methodological insight emerging from this body of work is that no single model or optimizer is universally superior. Instead, rainfall forecasting benefits from a layered approach where multiple paradigms are integrated. Some studies combined sequence learners like LSTM networks with gradient boosting machines to capture both temporal patterns and nonlinear tabular feature interactions. Others created ensembles of different classifiers or regressors and applied systematic grid search or architecture search to optimize them. These ensembles consistently outperformed individual models, confirming that model diversity provides resilience against variance and overfitting. More recent work has advanced this idea further, applying neural architecture search to design adaptive post-processing systems that calibrate ensemble forecasts, thereby correcting biases and improving reliability. Another striking feature of the recent literature is the explicit incorporation of large-scale climate drivers into rainfall models. In regions such as the Mediterranean, rainfall variability is strongly tied to teleconnection patterns like ENSO and the North Atlantic Oscillation. Models that integrated these indices alongside local meteorological data consistently outperformed those that ignored them. This demonstrates the importance of bridging local-scale prediction with global-scale climate drivers. Rainfall cannot be fully understood or predicted in isolation; it is a phenomenon deeply embedded in larger climatic systems. Models that recognize this multiscale character are better positioned to provide robust forecasts, especially as climate variability increases. The operationalization of rainfall detection and forecasting systems represents another key area of progress. While many studies focus on methodological accuracy, several have emphasized real-time applications. Machine learning models have been embedded in urban drainage management systems to provide actionable forecasts within operational timeframes, reducing flood risks in highly vulnerable urban settings. Other systems, like PERSIANN, have achieved global operational status, producing real-time precipitation estimates from satellite imagery for use in disaster management and hydrological research worldwide. These contributions demonstrate that rainfall forecasting research is not confined to the laboratory but is increasingly being translated into practical, real-world tools with tangible societal benefits. Interpretability has also become a priority. Advanced models, particularly deep learning systems, have faced criticism for their lack of transparency. To address this, researchers have begun incorporating explainability tools such as SHAP, which quantify the importance of different features in determining predictions. This allows stakeholders to understand not just what the model predicts but why it makes those predictions. In hydrology, where decisions about water management, flood risk, and agricultural planning carry significant economic and social weight, this transparency is critical. The move towards explainable AI reflects a recognition that accuracy alone is not sufficient; trust and accountability are equally necessary for widespread adoption. Interpretability and transparency will also remain central to future developments. Although explainability methods such as SHAP have been applied to some rainfall models, there is a need for more domain-specific interpretability tools. Future research should focus on developing explanation techniques that not only identify important predictors but also connect them to recognizable meteorological phenomena. For example, a model's identification of humidity or pressure as key variables should be contextualized within the dynamics of convection and storm formation. By producing explanations that resonate with domain knowledge, future models can bridge the gap between AI predictions and meteorological reasoning, thereby increasing trust and adoption in operational agencies. In conclusion, the future of rainfall detection and forecasting lies in integration and adaptability. The most promising systems will likely be those that combine multimodal data, embed physical constraints, employ adaptive optimization, ensure interpretability, and are designed for operational deployment under changing climate conditions. Addressing these challenges requires interdisciplinary collaboration across hydrology, computer science, meteorology, and decision science. With such efforts, rainfall forecasting can evolve into a mature, reliable, and indispensable tool for climate resilience and sustainable water management.

4. CONCLUSION

Rainfall detection and forecasting have evolved into a central research priority for hydrology, meteorology, and climate science due to their profound implications for disaster management, agriculture, water resources, and climate adaptation. The reviewed body of work illustrates a decisive methodological shift from traditional empirical and statistical models towards approaches that combine deep learning, metaheuristic optimization, ensemble learning, and climate-informed features. Each paradigm contributes unique strengths: deep learning excels at capturing spatiotemporal complexity, metaheuristics provide powerful tools for parameter optimization, ensembles enhance robustness, teleconnection indices bridge local and global climate scales, and explainability tools make forecasts more transparent and trustworthy. The studies reviewed demonstrate that rainfall forecasting is not a single-domain challenge but rather a problem requiring integration across methods and disciplines. Urban-focused models highlight the need for fine-scale predictions to mitigate flash flooding, while global systems show the importance of satellite-based estimation for regions lacking ground observations. Hybrid models reveal that optimization and machine learning are most powerful when used together, and ensemble systems underscore that diversity in modeling strategies produces more resilient forecasts. The cumulative lesson is that no single approach is sufficient; instead, the most promising advances come from hybridization, integration, and continual adaptation. Despite impressive progress, persistent challenges remain. Models must balance accuracy with interpretability, ensuring that forecasts can be both trusted and acted upon. Data scarcity continues to limit progress in regions with weak observational networks, requiring innovative solutions such as generative modeling, transfer learning, and federated learning. Climate change introduces additional uncertainty, making it essential for rainfall forecasting systems to be robust under non-stationary conditions and capable of adapting to new climatic regimes. Operationalization also remains a hurdle, as predictive advances must be translated into real-time systems that directly inform decisions in water management, urban drainage, and disaster preparedness. Looking forward, the trajectory of research points toward greater integration. Future rainfall forecasting systems will likely incorporate multimodal data streams, embed physical laws within data-driven models, apply adaptive optimization strategies, and ensure transparency through explainable AI. These systems must be computationally efficient, scalable across regions, and designed for real-world implementation. Moreover, evaluation frameworks should go beyond technical error metrics to consider decision-making outcomes, ensuring that advances in predictive science translate into tangible societal benefits. In conclusion, rainfall forecasting has entered a new era where artificial intelligence, optimization, and climate science converge to address one of the most complex and consequential elements of the hydrological cycle. The studies reviewed provide clear evidence that such integrated approaches significantly enhance predictive skill, resilience, and applicability. Continued progress will depend on interdisciplinary collaboration, methodological innovation, and an unwavering focus on operational and societal relevance. With these priorities, rainfall detection and forecasting can evolve into mature, reliable, and indispensable tools for building climate resilience and managing water resources in an uncertain future.

REFERENCES

[1] A. M. Elshewey, A. A. Alhussan, D. S. Khafaga, M. Radwan, E.-S. M. El-Kenawy, and N. Khodadadi, "An enhanced adaptive dynamic metaheuristic optimization algorithm for rainfall prediction depends on long short-term memory," *PLoS One*, vol. 20, no. 6, p. e0317554, 2025.

[2] B. T. Pham, K.-T. T. Bui, I. Prakash, and H.-B. Ly, "Hybrid artificial intelligence models based on adaptive neuro fuzzy inference system and metaheuristic optimization algorithms for prediction of daily rainfall," *Physics and Chemistry of the Earth, Parts A/B/C*, vol. 134, p. 103563, 2024.

[3] R. Kumar, M. P. Singh, B. Roy, and A. H. Shahid, "A Comparative Assessment of Metaheuristic Optimized Extreme Learning Machine and Deep Neural Network in Multi-Step-Ahead Long-term Rainfall Prediction for All-Indian Regions," *Water Resources Management*, vol. 35, no. 6, pp. 1927–1960, Apr. 2021.

[4] S. S. Sammen, O. Kisi, M. Ehteram, A. El-Shafie, N. Al-Ansari, M. A. Ghorbani, S. A. Bhat, A. N. Ahmed, and S. Shahid, "Rainfall modeling using two different neural networks improved by metaheuristic algorithms," *Environmental Sciences Europe*, vol. 35, no. 1, p. 112, Dec. 2023.

[5] S. Chaudhuri, S. Goswami, D. Das, and A. Middey, "Meta-heuristic ant colony optimization technique to forecast the amount of summer monsoon rainfall: skill comparison with Markov chain model," *Theoretical and Applied Climatology*, vol. 116, no. 3-4, pp. 585–595, May 2014.

[6] A. Malik, Y. Tikhamarine, D. Souag-Gamane, P. Rai, S. S. Sammen, and O. Kisi, "Support vector regression integrated with novel meta-heuristic algorithms for meteorological drought prediction," *Meteorology and Atmospheric Physics*, vol. 133, no. 3, pp. 891–909, Jun. 2021.

[7] B. Zerouali, F. Chebana, and T. B. M. J. Ouarda, "Ai systems optimized by metaheuristics and teleconnection indices for rainfall modeling," *Heliyon*, vol. 9, no. 4, 2023.

[8] Y. Qiao, H. Zhang, and L. Wang, "Metaheuristic evolutionary deep learning model for rainfall–runoff simulation," *Expert Systems with Applications*, vol. 229, p. 120616, 2023.

[9] W. Y. Lai, K. K. Kuok, S. Gato-Trinidad, M. R. Rahman, and M. K. Bakri, "Metaheuristic Algorithms to Enhance the Performance of a Feedforward Neural Network in Addressing Missing Hourly Precipitation," *International Journal of Integrated Engineering*, vol. 15, no. 1, pp. 273–285, 2023.

[10] A. Sen, A. R. Mazumder, D. Dutta, U. Sen, P. Syam, and S. Dhar, "Comparative Evaluation of Metaheuristic Algorithms for Hyperparameter Selection in Short-Term Weather Forecasting," in *Proceedings of the 15th International Joint Conference on Computational Intelligence*, 2023, pp. 238–245, arXiv:2309.02600 [cs].

[11] Z. Beheshti, M. Firouzi, S. M. Shamsuddin, M. Zibarzani, and Z. Yusop, "A new rainfall forecasting model using the CAPSO algorithm and an artificial neural network," *Neural Computing and Applications*, vol. 27, no. 8, pp. 2551–2565, Nov. 2016.

[12] F. Eslami and R. Kamali, "Developing machine learning models with metaheuristic algorithms for droplet size prediction in a microfluidic microchannel," *Swarm and Evolutionary Computation*, vol. 87, p. 101583, 2024.

[13] S. Mittal and O. P. Sangwan, "Metaheuristic Techniques Optimised LSTM Network for Improved Weather Prediction," in *2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI)*, vol. 2. IEEE, 2024, pp. 1–6.

[14] L. Penghui, A. A. Ewees, B. H. Beyaztas, C. Qi, S. Q. Salih, N. Al-Ansari, S. K. Bhagat, Z. M. Yaseen, and V. P. Singh, "Metaheuristic optimization algorithms hybridized with artificial intelligence model for soil temperature prediction: Novel model," *IEEE Access*, vol. 8, pp. 51 884–51 904, 2020.

[15] I. M. El-Hasnony, S. I. Barakat, and R. R. Mostafa, "Optimized ANFIS model using hybrid metaheuristic algorithms for Parkinson's disease prediction in IoT environment," *IEEE Access*, vol. 8, pp. 119 252–119 270, 2020.

[16] B. Roy, M. P. Singh, and A. Singh, "A novel approach for rainfall-runoff modelling using a biogeography-based optimization technique," *International Journal of River Basin Management*, vol. 19, no. 1, pp. 67–80, Jan. 2021.

[17] H. Y. Chong, H. J. Yap, S. C. Tan, K. S. Yap, and S. Y. Wong, "Advances of metaheuristic algorithms in training neural networks for industrial applications," *Soft Computing*, vol. 25, no. 16, pp. 11 209–11 233, Aug. 2021.

[18] E. H. Lee, "Groundwater level prediction using modified recurrent neural network combined with metaheuristic optimization algorithm," *Groundwater for Sustainable Development*, vol. 28, p. 101398, 2025.

[19] N. L. Kushwaha, J. Rajput, A. Elbeltagi, A. Y. Elnaggar, D. R. Sena, D. K. Vishwakarma, I. Mani, and E. E. Hussein, "Data intelligence model and meta-heuristic algorithms-based pan evaporation modelling in two different agro-climatic zones: a case study from Northern India," *Atmosphere*, vol. 12, no. 12, p. 1654, 2021.

[20] B. Marouane, M. A. Mu'azu, and A. Petroselli, "Prediction of reservoir evaporation considering water temperature and using ANFIS hybridized with metaheuristic algorithms," *Earth Science Informatics*, vol. 17, no. 2, pp. 1779–1798, Apr. 2024.

[21] Y. Wang and S. Razmjooy, "Prediction of drought hydrological and water scarcity based on optimal artificial intelligence by developing a metaheuristic optimization algorithm," *Physics and Chemistry of the Earth, Parts A/B/C*, vol. 135, p. 103669, 2024.

[22] A. Jaafari, S. V. R. Termeh, and D. T. Bui, "Genetic and firefly metaheuristic algorithms for an optimized neuro-fuzzy prediction modeling of wildfire probability," *Journal of environmental management*, vol. 243, pp. 358–369, 2019.

[23] P. Zhao, W. Liu, and M. Chen, "A deep learning model coupled with metaheuristic optimization for urban rainfall prediction," *Journal of Hydrology*, vol. 651, p. 132596, 2025.

[24] A. Nosratpour, R. Hosseini, and S. Karimi, "Satellite-based extreme precipitation estimation using aco-optimized mlp with cnn-derived inputs," *Journal of Hydrology*, 2025.

[25] E.-S. M. El-Kenawy, M. M. Eid, and A. Ibrahim, "Rainfall classification using adaptive dynamic puma optimizer and guided whale optimization," *Frontiers in Environmental Science*, 2024.

[26] S. S. Samman, O. Kisi, and M. Ehteram, "Rainfall modeling using neural networks improved by metaheuristic algorithms," *Environmental Sciences Europe*, vol. 35, p. 112, 2023.

[27] K. Paik, J. H. Kim, H. S. Kim, and D. R. Lee, "A conceptual rainfall-runoff model considering seasonal variation," *Hydrological Processes*, vol. 19, no. 19, pp. 3837–3850, Dec. 2005.

[28] V. K. Vidyarthi and S. Chourasiya, "Particle Swarm Optimization for Training Artificial Neural Network-Based Rainfall–Runoff Model, Case Study: Jardine River Basin," in *Micro-Electronics and Telecommunication Engineering*, D. K. Sharma, V. E. Balas, L. H. Son, R. Sharma, and K. Cengiz, Eds. Singapore: Springer Singapore, 2020, vol. 106, pp. 641–647.

[29] J. Manuel Guerrero-Valadez and F. Martínez-Rios, "Rain-Fall Optimization Algorithm with new parallel implementations." *Journal of Business & Projects/Revista de Gestão e Projetos*, vol. 11, no. 2, 2020.

[30] S. V. R. Termeh, K. Khosravi, M. Sartaj, S. D. Keesstra, F. T.-C. Tsai, R. Dijksma, and B. T. Pham, "Optimization of an adaptive neuro-fuzzy inference system for groundwater potential mapping," *Hydrogeology Journal*, vol. 27, no. 7, pp. 2511–2534, Nov. 2019.

[31] M. Alamgeer, A. Al-Rasheed, A. Alhindi, M. A. Hamza, A. Motwakel, and M. I. Eldesouki, "Data Mining with Comprehensive Oppositional Based Learning for Rainfall Prediction." *Computers, Materials & Continua*, vol. 74, no. 2, 2023.

[32] P. Lathika and D. S. Singh, "Stochastic Bayesian approach and CTSA based rainfall prediction in Indian states," *Modeling Earth Systems and Environment*, vol. 10, no. 3, pp. 3219–3228, Jun. 2024.

[33] T. Bostan, "Generating a landslide susceptibility map using integrated meta-heuristic optimization and machine learning models," *Sustainability*, vol. 16, no. 21, p. 9396, 2024.

[34] Z. Beheshti, M. Firouzi, S. M. Shamsuddin, M. Zibarzani, and Z. Yusop, "A new rainfall forecasting model using the CAPSO algorithm and an artificial neural network," *Neural Computing and Applications*, vol. 27, no. 8, pp. 2551–2565, Nov. 2016.

[35] F. Zhang, Q. Sun, M. Mehrabadi, B. Khoshnevisan, Y. Zhang, X. Fan, L. Zhai, Y. Xia, M. Wu, and D. Liu, "Joint analytical hierarchy and metaheuristic optimization as a framework to mitigate fertilizer-based pollution," *Journal of Environmental Management*, vol. 278, p. 111493, 2021.

[36] S. E. Priestly, K. Raimond, Y. Cohen, J. Brema, and D. J. Hemanth, "Evaluation of a novel hybrid lion swarm optimization–AdaBoostRegressor model for forecasting monthly precipitation," *Sustainable Computing: Informatics and Systems*, vol. 39, p. 100884, 2023.