Journal of Sustainable Development of Natural Resources Management

http://www.sdewes.org/jsdnarema

Year 2025, Volume 1, Issue 3, 1010617

Review Article

AI-Powered Water Management: Developing Infrastructure for a Future That Is Climate-Resilient

Iman Hajirad[*]
Department of Irrigation and Reclamation Engineering, Faculty of Agriculture and Natural Resources, University of Tehran, Karaj, Iran.
E-mail: i.hajirad@ut.ac.ir

Cite as: Hajirad, I., AI-Powered Water Management: Developing Infrastructure for a Future That Is Climate-Resilient, J. sustain. dev. nat. res. man., ONLINE FIRST (2025), 1010617, https://doi.org/10.13044/j.sdnarema.d1.0617

ABSTRACT

Climate change has introduced significant uncertainties in hydrological systems, such as erratic rainfall, prolonged droughts, and extreme weather events, which have challenged the efficacy of traditional water infrastructure and forecasting models. Conventional hydrological models, whether statistical or physical, often struggle to handle real-time variables, intricate relationships, and nonlinear dynamics. In this context, artificial intelligence (AI) emerges as a powerful, data-driven solution that consistently outperforms traditional methods in both accuracy and adaptability. This study systematically reviews the use of AI, specifically machine learning techniques like Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Random Forests, and Support Vector Machines (SVM), to predict critical hydrological variables such as river flow and groundwater levels. These models are highly capable of learning from noisy or incomplete data, making them particularly valuable for regions with limited monitoring infrastructure. A case study on river flow prediction demonstrates the superior performance of the LSTM model over the statistical ARIMA model, especially in accurately capturing peak flows during extreme events, with an NSE value of 0.87 compared to ARIMA's 0.68. The research also highlights the importance of climate-adaptive infrastructure planning. By integrating AI models with remote sensing data and IoT-enabled environmental monitoring systems, it is possible to create adaptive systems that can anticipate climate change impacts, optimize water storage and distribution, and respond effectively to real-time changes. This approach provides a robust framework for designing water infrastructure that is both flexible and resilient against long-term climatic shifts and short-term extreme events. Despite the transformative potential of AI, significant challenges remain, including data scarcity, algorithmic limitations such as high computational demands and the "black box" nature of some models, as well as ethical concerns regarding potential biases in resource distribution. This work addresses these challenges while emphasizing the promising opportunities presented by AI, including the optimization of water consumption and the development of risk-informed strategies. Ultimately, this paper advocates for an integrated and intelligent approach that redefines hydrological modeling and infrastructure design in the age of climate change.

KEYWORDS

AI, Hydrology, Climate Change, Water Management, Resilience.

[*] Corresponding author

INTRODUCTION

Climate change stands today as one of the most profound environmental challenges influencing the availability, distribution, and reliability of freshwater resources across the globe [1]. The intensification of climate variability manifesting in the form of unpredictable rainfall patterns, severe droughts, increased evapotranspiration, and heightened frequency of extreme weather events has rendered many traditional water management systems inadequate. These systems, largely based on historical data and static assumptions, are increasingly incapable of capturing the complex, non-linear, and evolving behavior of hydrological systems under changing climatic conditions. This growing complexity underscores the necessity for a paradigm shift in how water resources are modeled, managed, and planned. This is where intelligent, data-driven, and flexible frameworks become essential.

Traditional hydrological models, whether physical or statistical, often fail to respond dynamically to real-time changes or integrate diverse data sources such as satellite imagery, sensor networks, or climate forecasts. As a result, policymakers and engineers are left with outdated tools that cannot support robust decision-making under conditions of uncertainty. In recent years, Artificial Intelligence (AI) and Machine Learning (ML) techniques have shown great promise in addressing these shortcomings. A growing body of research literature demonstrates the superior performance of these tools in capturing non-linear relationships, handling incomplete datasets, and adapting to rapidly changing conditions. Review papers such as those by Biazar et al. [2], Asif et al. [3], and Ciampittiello et al. [4] have explored the application of AI for hydrological prediction, flood forecasting, and climate-informed water modeling. Other studies, like Brandão et al. [5] and Wang et al. [6], highlight hybrid approaches that combine ML with remote sensing data or IoT-based environmental monitoring systems. However, despite the advancements, a gap remains: most reviews treat modeling and infrastructure as separate disciplines, without fully considering how AI can act as a cohesive bridge between predictions and planning, particularly in the design of adaptive, climate-resilient water infrastructure. This growth demonstrates the increasing academic and practical interest in using AI for water management, which represents a major shift in research focus (Figure 1).

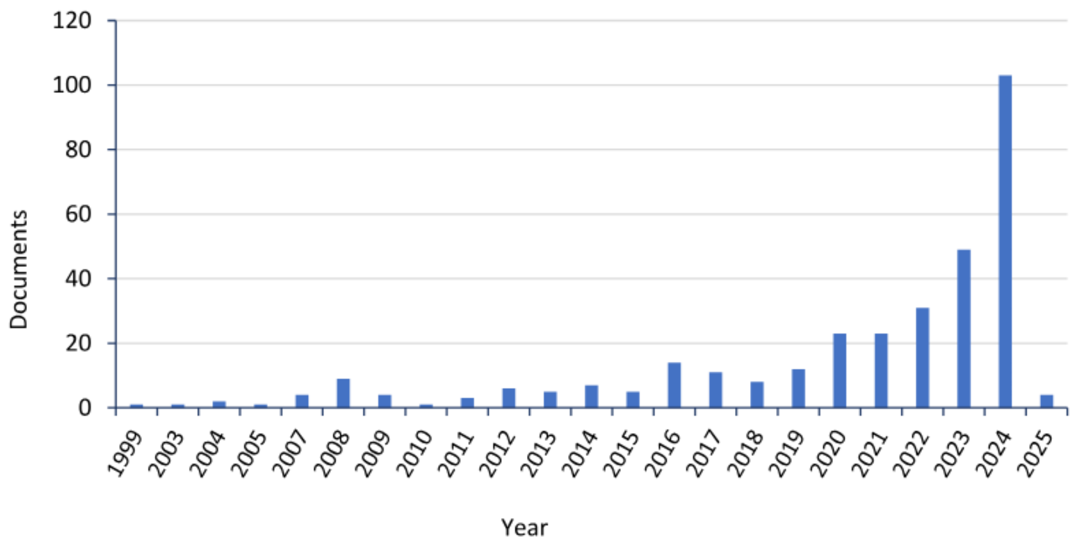

Figure 1. Annual number of scientific articles with the terms artificial intelligence, climate change, and water resource management [7]

Consequently, this review seeks to fill this gap by providing a comprehensive and interdisciplinary synthesis of how AI-powered models can not only improve hydrological predictions but also support the design of forward-looking infrastructure. It examines the integration of deep learning methods, including Long Short-Term Memory (LSTM), Support Vector Machines (SVM), Random Forests, and other models, with modern data sources such as satellite observations and IoT-enabled monitoring. Furthermore, this review investigates how these models can inform the design of dynamic infrastructure systems that can adapt to both long-term climate changes and short-term extreme events. The innovation of this review lies in its holistic approach. While previous literature often separates machine learning from infrastructure planning, this study emphasizes their interdependence in an era of climate crisis. By unifying the technical strengths of AI with the principles of resilience and adaptability, this paper offers a timely perspective that is both scientifically robust and practically actionable. As societies face unprecedented water challenges, this integrated approach provides a roadmap towards a sustainable, intelligent, and responsive water resource management system.

METHOD

This review article systematically synthesizes existing literature on the application of Artificial Intelligence (AI) in water management and infrastructure planning, specifically within the context of climate change resilience. The methodology employed for this review involved a comprehensive and structured approach to identify, select, and critically analyze relevant scholarly publications.

Literature Search Strategy

A broad and inclusive literature search was conducted across major academic databases, including Scopus, Web of Science, and Google Scholar, in addition to specialized journal platforms pertinent to hydrology, water resources management, artificial intelligence, and climate change. The search strategy utilized a combination of keywords such as "Artificial Intelligence," "AI," "Machine Learning," "Deep Learning," "Hydrology," "Water Management," "Water Resources," "Climate Change," "Adaptive Infrastructure," "Resilience," "River Flow Prediction," "Groundwater Levels," "Remote Sensing," and "IoT in Water Management." This approach aimed to capture a wide array of relevant studies, with a primary focus on peer-reviewed articles, review papers, and conference proceedings published predominantly within the last decade, prioritizing those that demonstrated practical applications and significant theoretical advancements in the field.

Selection Criteria

Following the initial search, a rigorous selection process was implemented based on predefined criteria to ensure the inclusion of highly relevant and impactful research. Articles were chosen for their direct contribution to understanding the intersection of AI and water management, with a particular emphasis on their relevance to climate change adaptation and infrastructure resilience. Inclusion criteria specifically targeted studies that utilized AI and machine learning techniques such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Random Forests, and Support Vector Machines (SVM) for hydrological modeling or prediction. Furthermore, studies discussing the integration of AI with remote sensing data, Internet of Things (IoT) technologies, or big data for water resource management were included. The selection also favored articles that addressed adaptive infrastructure planning in response to climate change, analyzed the challenges and opportunities associated with AI application in water resources, or presented empirical evidence and case studies on AI's performance in hydrological forecasting. Conversely, exclusion criteria were applied to non-peer-reviewed materials, studies focused purely on theoretical AI concepts without practical hydrological application, and articles not available in English.

Data Extraction and Synthesis

Upon selection, a detailed process of data extraction and synthesis was undertaken. Key information was meticulously extracted from each chosen article, encompassing details such as the specific AI models employed, the hydrological variables predicted, the data sources utilized, reported performance metrics, primary research findings, and identified challenges in AI implementation, and proposed solutions or future directions. This extracted data then underwent a systematic analysis to discern overarching themes, identify emerging trends, recognize significant advancements, and pinpoint existing knowledge gaps within the evolving field of AI in water management. This comprehensive synthesis facilitated the development of a holistic overview of the current state-of-the-art, thereby informing the subsequent discussions on the transformative potential of AI in fostering sustainable water management practices. The insights derived from this analytical process were then meticulously structured into logical sections throughout the review, ensuring a coherent, well-supported, and forward-looking perspective on the subject matter.

REVIEW OF TRADITIONAL HYDROLOGICAL MODELS

Fundamentals of hydrological modeling and traditional challenges

Hydrological modeling is an essential tool for sustainable water resource management. These models use geological, topographic, and climatic data to simulate processes of the water cycle, such as precipitation, runoff, evapotranspiration, and infiltration, to analyze a watershed's response to human or climatic changes. They are broadly categorized into two types: statistical (empirical) and process-based (physical) models, each with its own uses and limitations [8].

Physical models, which include SWAT, MIKE SHE, and HEC-HMS, use mathematical and physical relationships to depict how hydrological systems behave. While these models can faithfully replicate the behavior of natural systems, they often have drawbacks like high computational complexity and a strong dependence on data quality, which results in expensive processing and time. In contrast, statistical models, like regression or time series models such as ARIMA [9], are based on correlation-based relationships. Though easy to use and fast to compute, they frequently fall short in dynamic and nonlinear situations [10]. The inherent shortcomings of conventional models have become increasingly apparent in the age of climate change. These models mostly rely on past data and fixed assumptions, revealing their weaknesses in handling new conditions and extreme events. The large number of adjustable parameters and high sensitivity to input data make calibration a difficult and unpredictable procedure, especially in data-scarce areas. Furthermore, empirical models are limited in their ability to adapt to the dynamic realities of contemporary watersheds due to their inability to represent intricate, nonlinear connections among variables [11]. Ultimately, a major flaw in both conventional methods is their inability to incorporate several modern data sources, including satellite imagery, real-time Internet of Things (IoT) data, and big data related to climate change. This limitation reduces their ability to adapt to today’s more complicated circumstances. In this regard, implementing cutting-edge techniques like artificial intelligence and machine learning creates new opportunities for hydrological modeling, more precise forecasting, and infrastructure-focused decision-making.

Comparison of AI-Based and Conventional Hydrological Models

While traditional models like ARIMA and physical models are foundational to hydrological science, their limitations in an era of climate change have become increasingly evident. AI-based models, such as Long Short-Term Memory (LSTM), have demonstrated superior performance in several key areas, particularly when dealing with the complex, non-linear dynamics of modern hydrological systems. Table 1 provides a detailed comparison, highlighting how AI models offer enhancements in accuracy, efficiency, and adaptability.

Table 1. Comparison of AI-Based and Conventional Hydrological Models

Aspect	Conventional Hydrological Models (e.g., ARIMA, SWAT)	AI-Based Hydrological Models (e.g., LSTM, ANN)
Accuracy	Often struggle to capture nonlinear dynamics and peak flows during extreme events. Their NSE value is typically lower, as seen in the case study where ARIMA scored 0.68.	Consistently outperform traditional methods, especially in capturing non-linear relationships and peak flows. The LSTM model, for example, achieved an NSE value of 0.87.
Data Handling	Highly dependent on clean, complete, and high-quality data. Incomplete or noisy datasets can lead to significant inaccuracies.	Highly capable of learning from noisy, incomplete, or scattered data, making them valuable for data-scarce regions.
Computational Efficiency	Physical models like SWAT can have high computational demands and long processing times. Statistical models like ARIMA are faster to compute.	Can have high computational demands, especially for complex deep learning models like DNNs. However, once trained, they can provide rapid, real-time predictions.
Adaptability	Largely based on historical data and fixed assumptions, making them less effective in the face of evolving climate conditions and extreme events.	Can adapt to rapidly changing conditions by incorporating real-time data from sources like remote sensing and IoT devices. They can simulate system behavior under various climate scenarios.
Data Integration	Limited in their ability to incorporate diverse, modern data sources such as real-time IoT data or satellite imagery.	Seamlessly integrate various data sources, including satellite imagery (e.g., Landsat, MODIS) and IoT-enabled environmental monitoring systems.

REVIEW OF AI-BASED HYDROLOGICAL MODELS. THE ROLE OF ARTIFICIAL INTELLIGENCE IN ENHANCING HYDROLOGICAL MODELS

Due to the growing complexity of hydrological systems caused by climate change, traditional modeling techniques have faced significant challenges. Models based mainly on physical equations or traditional statistical methods often lack the accuracy needed for complex, nonlinear situations because they rely on highly precise inputs, require numerous calibration parameters, and incorporate various simplifications. A new and effective approach to this problem is the use of artificial intelligence (AI), specifically machine learning (ML) and artificial neural networks (ANNs). These models can uncover hidden patterns in large and irregular datasets without requiring prior knowledge of physical correlations, leading to highly accurate predictions [6]. A key advantage of AI-based models is their ability to handle noisy, scattered, and incomplete data. Unlike process-based models that use physical correlations to simulate phenomena like evaporation and runoff, ML models can learn and replicate system behavior based solely on historical data, which is especially useful in data-scarce areas [5]. ML algorithms like Random Forest and Support Vector Regression (SVR) can simulate complex, nonlinear interactions, a clear advantage over traditional statistical methods that assume linear relationships. Furthermore, ANNs and advanced variants like Long Short-Term Memory (LSTM) networks can predict time-dependent variables like river flow and precipitation with remarkable accuracy, often outperforming conventional models. ANNs are one of the most widely used methods for hydrological modeling because they can learn intricate correlations between inputs and outputs without needing explicitly stated relationships [3]. Random Forest models are considered dependable for water resource prediction and classification due to their tree-based structure and resistance to over fitting, providing stable and noise-resistant estimates. Similarly, the highly optimized XGBoost system has shown successful and accurate performance in forecasting phenomena like precipitation and floods [3]. SVR and Support Vector Machines (SVMs) are also excellent choices for situations with sparse or noisy datasets, as they provide powerful capabilities for differentiating between various hydrological circumstances by constructing nonlinear decision boundaries. Meanwhile, LSTM models are effective tools for time series forecasting of variables like stream flow and rainfall because they can capture long-term temporal dependencies, an area where conventional models typically fall short. Ultimately, using artificial intelligence in hydrological modeling improves accuracy, adaptability, and flexibility to changing climate circumstances, making these intelligent models crucial tools for the design and management of water-related systems in the twenty-first century [6].

REVIEW OF AI APPLICATIONS IN RIVER FLOW PREDICTION. RIVER FLOW PREDICTION USING ARTIFICIAL INTELLIGENCE-BASED MODELS

Planning for watershed development, flood warning systems, sustainable dam operations, and the best possible use of water resources all depend on accurate river flow forecasting. Artificial Intelligence (AI)-based models have become viable substitutes for conventional statistical and physical methods due to improvements in machine learning algorithms and easier access to quantifiable data, especially when hydrological data is noisy, uncertain, or incomplete [12]. A case study on river flow prediction clearly demonstrates the superior performance of AI models over traditional methods. For instance, in a comparison between the Long Short-Term Memory (LSTM) network and the statistical ARIMA model, the LSTM model achieved an NSE value of 0.87 on test data, while the ARIMA model only reached 0.68. This quantitative difference is significant and highlights a key advantage: the LSTM model was notably more accurate at identifying and capturing peak flows during extreme events, a crucial capability where traditional models often fall short.

Choosing the right input data is the first stage in the modeling process. The most dependable sources of information on precipitation, temperature, relative humidity, evapotranspiration, groundwater levels, and river discharge are usually hydrometric stations or remote sensing data. Incomplete, noisy, or outlier data must be rectified using techniques like statistical interpolation, Kalman filters, or moving averages to keep the model's accuracy from declining. Improving the prediction accuracy is largely dependent on the completeness and quality of the data [13]. One crucial phase in the creation of machine learning models is preprocessing. This step involves normalizing the data and separating them into test, validation, and training sets, usually with ratios like 70/15/15. The type of data and the prediction goal determine which learning method is used. The Long Short-Term Memory (LSTM) network was employed in this investigation because it is well suited for hydrological time series and can capture long-term temporal dependencies and nonlinear interactions. The Adam algorithm with the Mean Squared Error (MSE) loss function was used to train the intended model, which included LSTM layers, dropout layers, and an output layer [14].

Metrics including the coefficient of determination (R2), RMSE, NSE, and MAE were employed to assess the model's performance. The results from the LSTM model indicated a high capability for reconstructing river flow patterns. For example, the ARIMA statistical model only achieved an NSE value of 0.68 on test data, whereas the LSTM model's was 0.87. Furthermore, traditional models had trouble anticipating these abrupt variations, but the LSTM model was better at identifying flow peaks [15].

In conclusion, there are a number of benefits to using AI models like LSTM for river flow prediction over traditional techniques, particularly when there are nonlinear correlations between variables and the data is erratic or partial. However, the quality of the input data, the choice of suitable parameters, and the training procedure all have a significant impact on how well these models perform. The creation of hybrid and adaptable models for future water resource management may be made possible by combining these methods with physical models and climatic scenario analysis.

REVIEW OF AI-DRIVEN ADAPTIVE INFRASTRUCTURE. ADAPTIVE APPROACH TO WATER INFRASTRUCTURE PLANNING

Planning for water infrastructure is facing more and more difficulties in the modern day, including climate change, sharp variations in rainfall, and unforeseen spikes in water demand. In order to respond appropriately to environmental uncertainties, these conditions necessitate a change in the design and management of water resources. As a new tactic in this regard, the adaptive approach provides ways to effectively handle these uncertainties and complexities [16]. Systems and structures that are dynamic and flexible enough to react to shifting climatic, economic, and environmental situations are referred to as adaptive infrastructure. These infrastructures are designed in such a way that they can adapt to unforeseen changes without the need for complete reconstruction. When we take into account alterations in precipitation patterns, evaporation, rising temperatures, and the frequency of extreme droughts and floods all of which impair the operation of conventional water infrastructure the significance of this idea becomes clear [17].

According to this concept, infrastructure is designed to guarantee that systems are resilient to long-term climate shifts in addition to meeting immediate needs. This kind of design is based on the essential idea of "flexibility." In order to accomplish this, the behavior of water systems under various climatic conditions is simulated using AI-based prediction models. For example, machine learning algorithms can forecast when droughts or floods will occur and modify resource distribution or storage capabilities accordingly [18]. In order to put this strategy into practice, modern technologies like smart sensor networks and the Internet of Things (IoT) are essential. These systems make it possible to monitor environmental data in real time, which enables automatic reactions and prompt change detection. This avoids serious water resource emergencies by ensuring that management decisions are founded on accurate, current, and location-based information [19].

There are difficulties in putting the adaptive strategy into practice, despite its many benefits. The limitations of local-scale climate projections are one of the main obstacles. Planning is further complicated by the possibility that shifting social and economic factors will have an impact on water resources. Some of these issues have been resolved, though, thanks to the creation of innovative big data analysis tools and the application of sensors, satellite data, and AI-based prediction models [20].

In the end, it can be said that one of the best ways to manage water resources sustainably in the face of climate change is to use an adaptive strategy when constructing water infrastructure. This strategy not only makes water systems more resilient and less susceptible to climate-related hazards, but it also opens up possibilities for resource waste reduction, efficiency enhancement, and sustainable growth.

REVIEW OF AI INTEGRATION WITH CLIMATIC AND REMOTE

Integration of ai modeling with climatic and remote sensing data

In hydrological modeling, climate and remote sensing data are essential information sources. The study and forecasting of the behavior of water resources has seen a significant change in the last few decades due to the convergence of this data with AI-based models. This method improves the prediction capacities of water systems and increases modeling accuracy, especially in areas with complicated environmental circumstances or insufficient data [21,22].

A wealth of information regarding surface features, vegetation cover, soil moisture, evaporation, and surface temperature can be found in remote sensing data, particularly satellite photography from sensors like Landsat, MODIS, and Sentinel. These data help analyze changes in water resources over time and are used as inputs for hydrological models. For instance, Landsat imagery is essential for reconstructing hydrological patterns because it can precisely detect changes in land cover, rivers, and lakes [23]. The examination of this data necessitates sophisticated computational techniques due to their enormous volume and complexity. Artificial neural networks and machine learning techniques are used in this context to find the intricate and nonlinear correlations between hydrological variables and remote sensing data. In particular, satellite image analysis using Convolutional Neural Networks (CNN) has shown great efficacy in forecasting rainfall patterns, droughts, and shifts in water resources [24]. Internet of Things (IoT) technology is an important contemporary instrument for environmental monitoring in water resource management, in addition to remote sensing data. IoT sensors have the ability to gather data in real time on a variety of scales, including water flow, temperature, humidity, and water quality. These data have great informational value and can be combined with AI-based models to improve systems' predictive power, particularly in remote locations where traditional data is unavailable [25]. In this framework, machine learning models may be used more accurately thanks to the usage of Big Data systems, which compile various data from IoT sensors, ground stations, and remote sensing. Using sophisticated data mining techniques to analyze these data can greatly aid in spotting patterns in the changes of water resources, forecasting calamities like floods or droughts, and enhancing decision-making [26].

In the end, there is a great deal of promise for improving intelligent water resource management in the context of climate change by combining remote sensing data with AI-based hydrological forecasting models. Better prediction accuracy, efficient use of resources, and data-driven management choices based on current and trustworthy information are all results of this technological convergence.

Challenges and Opportunities in Using AI for Adaptive Modeling and Planning of Water Infrastructure

Even though artificial intelligence has the potential to revolutionize water resource management, there are a number of barriers to its widespread adoption and implementation, ranging from data-related and technical problems to organizational and ethical issues. A comprehensive understanding of these barriers is necessary to develop strategies that effectively overcome them and fully utilize AI's potential. Success in this field necessitates a comprehensive and diversified strategy, as illustrated by Figure 2, which offers a thorough review of key enabling variables and impediments. To lay a strong basis for upcoming conversations and focused study, each of these opportunities and obstacles will be looked at in greater detail in the sections that follow.

Data Issues and Algorithmic Limitations

The absence of precise, thorough, and trustworthy data is one of the main obstacles to applying artificial intelligence (AI) for hydrological modeling and adaptive planning of water infrastructure. The data needed in this discipline is frequently complicated, location- and time-dependent, and includes a lot of multivariate data, necessitating careful preparation, cleaning, and gathering methods. However, data is frequently lacking, dispersed, or prone to measurement mistakes in many places, particularly in developing nations. Inaccurate analysis and decreased accuracy of AI models can result from missing data on precipitation, temperature, evaporation, and river flow [18]. Another major obstacle to the efficient application of AI in this field is algorithmic restrictions. High processing power and access to robust processing infrastructure are necessary for complex models such as deep neural networks (DNN) and deep learning algorithms. It is difficult to apply these models in environments with constrained hardware resources. Furthermore, a large number of these algorithms function as "black boxes," meaning that end users are unable to understand their internal decision-making processes. In natural resource management, where decision-making necessitates traceability and openness, this becomes particularly difficult [27].

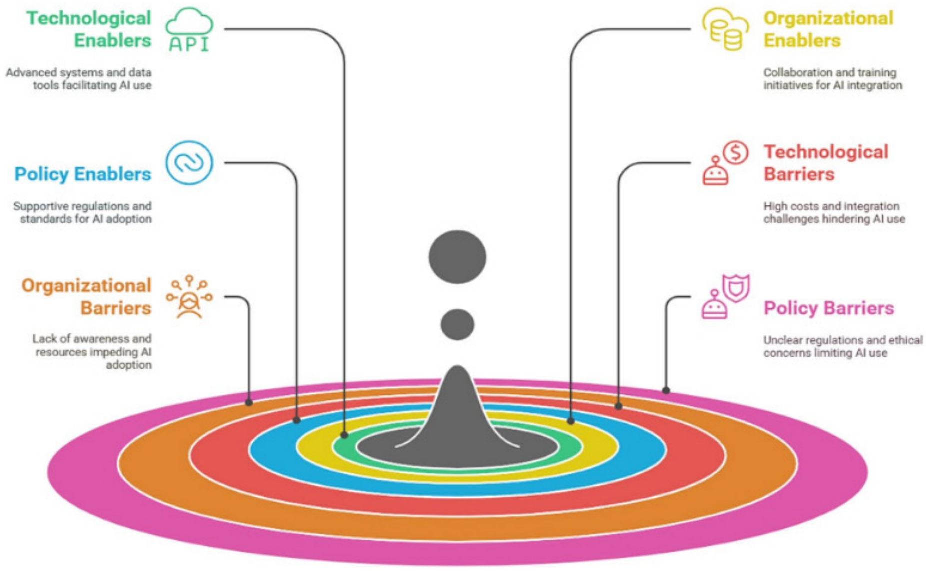

Figure 2. Key enabling factors and barriers influencing the widespread adoption of AI in water management [7]

Ethical and Social Considerations in the Use of AI

The application of AI to hydrological modeling and adaptive water infrastructure planning also presents ethical and societal issues. As previously stated, data quality issues, such as missing or untrustworthy data, continue to be a major worry [28]. However, algorithmic constraints also pose a significant obstacle to the successful implementation of AI in water resource management. AI models, especially deep learning algorithms, frequently display biases that result in unfair resource distribution or the omission of underserved communities. When these prejudices go unnoticed or unaddressed, ethical issues emerge because they may have detrimental social effects, particularly in areas that are disadvantaged and heavily reliant on water supplies. In order to overcome these obstacles, fair, interpretable, and transparent AI systems that guarantee the equitable and moral allocation of water resources must be developed [29].

Novel Opportunities in AI for Water Resource Management

Notwithstanding the difficulties, using AI to water infrastructure modeling and adaptive planning offers a number of promising prospects. AI is a potent tool for monitoring water resources, modeling climate change scenarios, and forecasting resource availability and consumption trends due to its capacity to process and interpret huge, complicated datasets. It is feasible to create adaptive models that react to shifting climatic conditions and facilitate speedier responses to calamities like floods or droughts by utilizing sophisticated algorithms [30]. Furthermore, by examining consumption trends and assessing the effectiveness of infrastructure systems, AI can help optimize the use of water resources. This is particularly important in areas with limited resources, like the Middle East, where AI-driven optimization can improve water system resilience and decrease water wastage. In the end, AI-powered intelligent modeling can open the door to creating climate-resilient infrastructure that can adjust to unanticipated circumstances [31].

DISCUSSION

The literature review reveals a significant shift in hydrological modelling and water infrastructure planning, driven by the uncertainties of climate change. Traditional models, whether statistical or physical, struggle with real-time variables, complex relationships, and the nonlinear dynamics of modern hydrological systems. This is particularly evident in the face of unpredictable rainfall, prolonged droughts, and extreme weather events, which highlights the urgent need for more accurate and adaptive predictive tools. Artificial Intelligence (AI) has emerged as a powerful solution to these challenges. Models like Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Random Forests, and Support Vector Machines (SVM) excel at extracting complex patterns from large-scale hydrological data. Their ability to learn from noisy, incomplete, or dispersed datasets is a crucial advantage, especially in regions with limited monitoring infrastructure. The case study showing LSTM's superior performance over the statistical ARIMA model in predicting river flow and capturing peak flows during extreme events, with an NSE value of 0.87 compared to ARIMA's 0.68, directly supports this trend. This shift moves us from models based on fixed assumptions and historical data to more dynamic and adaptable predictive frameworks. The literature strongly advocates for a climate-adaptive approach to water infrastructure, which is increasingly enabled by AI. This concept focuses on systems that can dynamically respond to changing conditions, maintaining long-term efficiency and withstanding climate shocks without requiring full reconstruction. AI-based prediction models are key here, as they can simulate water system behavior under various climate scenarios and forecast events like droughts or floods to optimize resource distribution and storage. The integration of AI with remote sensing data (e.g., from Landsat, MODIS, Sentinel) and IoT-enabled monitoring systems further enhances this adaptive capacity by providing real-time, location-based information for proactive decision-making. Despite this potential, there are significant challenges to the widespread adoption of AI in water management. Data scarcity and quality remain major obstacles, especially in developing nations where a lack of precise data can lead to inaccurate models. Algorithmic limitations are also a hurdle; complex deep learning models require high computational power, and their "black box" nature can hinder transparency in decision-making. Furthermore, ethical concerns, such as potential biases in AI models leading to unfair resource distribution, highlight the need for fair, interpretable, and transparent AI systems. Protecting the privacy of sensitive data collected via IoT is another critical ethical consideration. However, these challenges are balanced by promising opportunities. AI's ability to process and interpret vast datasets can be used to monitor water resources and optimize consumption trends, which is particularly vital in water-scarce regions. The collective evidence suggests that AI-powered intelligent modeling is not just an enhancement but a fundamental requirement for creating climate-resilient water infrastructure. Therefore, addressing the identified challenges through better data collection, investment in computational infrastructure, and the development of ethical frameworks will be crucial to realizing AI's full potential in sustainable water resource management.

CONCLUSION

Summary

The escalating complexities in water resource management, driven by climate change, demand a fundamental shift from traditional hydrological models and infrastructure planning. This review has highlighted the significant limitations of conventional models, which often fail to handle the intricate, nonlinear dynamics of contemporary hydrological systems during erratic rainfall and extreme weather events. In contrast, AI offers a transformative, data-driven solution that consistently outperforms traditional methods in accuracy and adaptability.

A central finding of this review is the remarkable effectiveness of machine learning techniques like ANN, LSTM, Random Forests, and SVM in predicting key hydrological variables such as river flow and groundwater levels. These models are especially valuable in data-scarce regions due to their ability to learn from incomplete or noisy data. The superior performance of LSTM in capturing peak flows, as demonstrated in the case study, exemplifies AI's capacity to handle dynamic scenarios where traditional models like ARIMA fall short.

The review also identifies a clear trend towards integrating AI with advanced data sources, including remote sensing (e.g., Landsat, MODIS, and Sentinel) and IoT-enabled environmental monitoring. This integration is key to developing adaptive infrastructure that can anticipate climate change impacts, optimize water distribution, and respond effectively to real-time changes. The concept of "adaptive infrastructure," which prioritizes resilience and flexibility, is therefore a core enabler for sustainable water management in a changing climate.

Despite these advancements, key challenges persist. The primary issue is the scarcity and quality of data, particularly in developing nations, which can lead to model inaccuracies. Algorithmic limitations, such as high computational demands and the "black box" nature of some models, also present hurdles. Furthermore, ethical and social considerations, including potential biases that could lead to unfair resource distribution, necessitate the development of fair and transparent AI systems.

To move forward, several recommendations are essential. Firstly, governments and organizations should invest more in collecting high-quality hydrological and climate data, augmented by remote sensing and IoT systems. Secondly, leveraging cloud computing and distributed processing can address the high computational demands of AI models. Thirdly, new AI models must be designed with social justice principles to ensure equitable water resource distribution, while data privacy is protected through techniques like encryption. Finally, establishing training programs for professionals is crucial to build a skilled workforce capable of utilizing these cutting-edge technologies. By addressing these challenges, we can fully realize AI's potential to transform water resource management into an intelligent, sustainable, and climate-resilient system for the future.

Recommendations

A number of useful and doable suggestions stand out in order to leverage artificial intelligence (AI) in water resource management and tackle the issues brought on by climate change. The availability of precise and current data is one of the most important requirements for the successful deployment of AI. More funding should be allocated by governments and organizations to the collection of climate and hydrological data, particularly in regions with limited data. Data accuracy can be greatly improved by establishing sophisticated monitoring systems with the use of remote sensing and the Internet of Things (IoT). To make more accurate forecasts, AI models should be regularly trained. To increase the accuracy and applicability of models, efforts should also be made to modify them using regional conditions and local data. Cloud infrastructure and distributed processing can improve the speed and efficiency of AI models, which are computationally intensive. This makes it possible for models to be used more widely and react instantly to forecasts. Models must be created using social justice concepts in order to avoid disparities in the distribution of water resources. Furthermore, it is crucial to protect the privacy of data gathered through the Internet of Things (IoT) and to use encryption techniques for data protection. A trained workforce is necessary for the application of AI in this field. To introduce them to cutting-edge technology and facilitate their efficient use, training programs for engineers, data analysts, and specialists in water resources should be established. These suggestions can successfully handle the difficulties brought on by climate change and contribute to the development of an intelligent and sustainable system for managing water resources.

REFERENCES

1. P. Pourmohammad and I. Hajirad, "Innovative Irrigation Practices for Sustainable Agriculture: Environmental Benefits and Implementation Challenges", J. Sustain. Dev. Nat. Resour. Manag., Vol. 1, No. 2, Art. no. 1010601, 2025, https://doi.org/10.13044/j.sdnarema.d1.0601.

2. S. M. Biazar, G. Golmohammadi, R. R. Nedhunuri, S. Shaghaghi, and K. Mohammadi, “Artificial Intelligence in Hydrology: Advancements in Soil, Water Resource Management, and Sustainable Development,” Sustainability, Vol. 17, No. 5, Art. no. 2250, 2025, https://doi.org/10.3390/su17052250.
3. M. Asif, M.M. Kuglitsch, I. Pelivan, and R. Albano. “Review and Intercomparison of Machine Learning Applications for Short-term Flood Forecasting”, Water Resources Management, Vol. 39, pp. 1971–1991, 2025, https://doi.org/10.1007/s11269-025-04093-x.
4. M. Ciampittiello, A. Marchetto, and A. Boggero, “Water resources management under climate change: A review”, Sustainability, Vol. 16, No. 9, Art. No.3590, 2024, https://doi.org/10.3390/su16093590.
5. A.R. Brandão, F.C. de Menezes Filho, P.T. Oliveira, and M.C. Fava, “Artificial neural networks applied for flood forecasting in ungauged basin–the Paranaíba river study case”, Proceedings of IAHS, Vol. 386, pp. 81-86, 2024, https://doi.org/10.5194/piahs-386-81-2024.
6. C. Wang, S. Jiang, Y. Zheng, F. Han, R. Kumar, O. Rakovec, S. Li, “Distributed hydrological modeling with physics‐encoded deep learning: A general framework and its application in the Amazon”, Water Resources Research, Vol. 60, No. 4, Art. no. e2023WR036170, 2024, https://doi.org/10.1029/2023WR036170.
7. L. Abdulameer, M. S. Al-Khafaji, A. T. Al-Awadi, N. M. L. Al Maimuri, M. Al-Shammari, A. N. Al-Dujaili, and DhiyaAl-Jumeily, “Artificial Intelligence in Climate-Resilient Water Management: A Systematic Review of Applications, Challenges, and Future Directions”, Water Conserv Sci Eng, Vol. 10, No. 1, Art. no. 44, 2025, https://doi.org/10.1007/s41101-025-00371-2.
8. State of Global Water Resources 2023 Report. https://library.wmo.int/viewer/69033/download?file=WMO-1362-2023_en.pdf&type=pdf&navigator=1, ISBN 978-92-63-11362-7, [Accessed: 12-September-2025].
9. Introducing ARIMA models. https://www.ibm.com/think/topics/arima-model, [Accessed: 12-September-2025].
10. S. Gegenleithner, M. Pirker, C. Dorfmann, R. Kern, and J. Schneider, “Long short-term memory networks for enhancing real-time flood forecasts: a case study for an underperforming hydrologic model”. Hydrology and Earth System Sciences, Vol. 29, No. 7, pp. 1939-1962, 2025, https://doi.org/10.5194/hess-29-1939-2025.
11. J.-L. Martel, F. Brissette, R. Arsenault, R. Turcotte, M. Castañeda-Gonzalez, W. Armstrong, E. Mailhot, J. Pelletier-Dumont, G. Rondeau-Genesse, and L.-P. Caron, “Assessing the adequacy of traditional hydrological models for climate change impact studies: a case for long short-term memory (LSTM) neural networks”, Hydrol. Earth Syst. Sci., vol. 29, No. 13, pp. 2811–2836, 2025, https://doi.org/10.5194/hess-29-2811-2025.
12. A. Khandelwal, S. Xu, X. Li, X. Jia, M. Stienbach, C. Duffy, J. Nieber, and V. Kumar, “Physics Guided Machine Learning Methods for Hydrology.” arXiv, 2020, https://doi.org/10.48550/arXiv.2012.02854.
13. X. Jia, J. Zwart, J. Sadler, A. Appling, S. Oliver, S. Markstrom, J. Willard, S. Xu, M. Steinbach, J. Read, and V. Kumar, “Physics-Guided Recurrent Graph Networks for Predicting Flow and Temperature in River Networks.” arXiv, 2020, https://doi.org/10.48550/arXiv.2009.12575.
14. W. Li, A. Kiaghadi, and C. Dawson, “High temporal resolution rainfall–runoff modeling using long-short-term-memory (LSTM) networks”, Neural Computing and Applications, Vol. 33, No. 4, pp. 1261-1278, 2021, https://doi.org/10.1007/s00521-020-05010-6.

15. M. Gauch, F. Kratzert, D. Klotz, G. Nearing, J. Lin, and S. Hochreiter, “Rainfall–runoff prediction at multiple timescales with a single Long Short-Term Memory network”, Hydrol. Earth Syst. Sci., Vol. 25, No. 4, pp. 2045–2062, 2021, https://doi.org/10.5194/hess-25-2045-2021.
16. B. Gersonius, R. Ashley, A. Pathirana, and C. Zevenbergen, “Climate change uncertainty: building flexibility into water and flood risk infrastructure,” Climatic Change, Vol. 116, No. 2, pp. 411–423, 2013, https://doi.org/10.1007/s10584-012-0494-5.
17. C.-N. Roukounis, “Evaluation of the impacts of climate change on coastal water systems and infrastructure, and measures for adaptation and management,” National Technical University of Athens (NTUA), School of Agricultural and Surveying Engineers - Geoinformatics Engineers, Department of Infrastructure and Rural Development Projects, Laboratory of Land Improvement Projects & Water Resources Management, 2024 (Doctoral Dissertation), https://doi.org/10.12681/eadd/57506.
18. R. Muñoz-Carpena, A. Carmona-Cabrero, Z. Yu, G. Fox, and O. Batelaan, “Convergence of mechanistic modeling and artificial intelligence in hydrologic science and engineering”, PLOS Water, Vol. 2, No. 8, Art. no. e0000059, 2023, https://doi.org/10.1371/journal.pwat.0000059.
19. M. Mohammadi, G. Assaf, R. H. Assaad, and A. “Jasmine” Chang, “An Intelligent Cloud-Based IoT-Enabled Multimodal Edge Sensing Device for Automated, Real-Time, Comprehensive, and Standardized Water Quality Monitoring and Assessment Process Using Multisensor Data Fusion Technologies,” J. Comput. Civ. Eng., vol. 38, no. 6, p. 04024029, 2024, https://doi.org/10.1061/JCCEE5.CPENG-5989.
20. N. Nagpal, H. H. Alhelou, P. Siano, P. Sanjeevikumar, and D. Lakshmi, Eds., Applications of Big Data and Artificial Intelligence in Smart Energy Systems: Volume 2: Energy Planning, Operations, Control and Market Perspectives. RIVER PUBLISHERS / Routeledge, Gistrup, Denmark; New York, NY, USA, 2023, https://doi.org/10.1201/9781003440864.
21. F. Kratzert, D. Klotz, G. Shalev, G. Klambauer, S. Hochreiter, and G. Nearing, “Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets”, Hydrol. Earth Syst. Sci., Vol. 23, No. 12, pp. 5089–5110, 2019, https://doi.org/10.5194/hess-23-5089-2019.
22. A. Sunil, B. Deepthi, A. B. Mirajkar, and S. Adarsh, “Modeling future irrigation water demands in the context of climate change: a case study of Jayakwadi command area, India,” Model. Earth Syst. Environ., vol. 7, no. 3, pp. 1963–1977, Sep. 2021, https://doi.org/10.1007/s40808-020-00955-y.
23. A. Amazirh, O. Merlin, and S. Er-Raki, “Including Sentinel-1 radar data to improve the disaggregation of MODIS land surface temperature data”, ISPRS Journal of Photogrammetry and Remote Sensing, Vol. 150, pp. 11–26, 2019, https://doi.org/10.1016/j.isprsjprs.2019.02.004.
24. H. Hammouch, M. A. El-Yacoubi, H. Qin, and H. Berbia, “A Systematic Review and Meta-Analysis of Intelligent Irrigation Systems”, IEEE Access, Vol. 12, pp. 128285–128304, 2024, https://doi.org/10.1109/ACCESS.2024.3421322.
25. T. Almaaitah, D. Joksimovic, and T. Sajin, “Real-Time IoT-Enabled Water Management for Rooftop Urban Agriculture Using Commercial Off-the-Shelf Products”, The 1st International Online Conference on Agriculture — Advances in Agricultural Science and Technology, 2022, Vol. 10, No. 1, Art. no. 34, https://doi.org/10.3390/IOCAG2022-12235.
26. S. Puttinaovarat and P. Horkaew, “Flood Forecasting System Based on Integrated Big and Crowdsource Data by Using Machine Learning Techniques”, IEEE Access, Vol. 8, pp. 5885–5905, 2020, https://doi.org/10.1109/ACCESS.2019.2963819.

27. K. Yokoo, K. Ishida, A. Ercan, T. Tu, T. Nagasato, M. Kiyama, and M. Amagasaki, "Capabilities of deep learning models on learning physical relationships: Case of rainfall-runoff modeling with LSTM", Science of The Total Environment, Vol. 802, Art. no. 149876, 2022, https://doi.org/10.1016/j.scitotenv.2021.149876.
28. L. Zhong, H. Lei, Z. Li, and S. Jiang, "Advancing streamflow prediction in data-scarce regions through vegetation-constrained distributed hybrid ecohydrological models", Journal of Hydrology, Vol. 645, Art no. 132165, 2024, https://doi.org/10.1016/j.jhydrol.2024.132165.
29. F. Cappelli, Interpretability of machine learning with hydrological applications, PhD Thesis, Università Commerciale "Luigi Bocconi", Milan, Italy, 2023, https://iris.unibocconi.it/handle/11565/4058507, [Accessed: 12-September-2025].
30. I. Ashraf, A. Artelt, and B. Hammer, "Scalable and Robust Physics-Informed Graph Neural Networks for Water Distribution Systems", arXiv, 2025, https://doi.org/10.48550/arXiv.2502.12164.
31. . Yang, P. Li, T. Li, A. Wierman, and S. Ren, "Learning-Augmented Online Control for Decarbonizing Water Infrastructures", arXiv, 2025, https://doi.org/10.48550/arXiv.2501.14232.

Paper submitted: 25.06.2025
Paper revised: 29.08.2025
Paper accepted: 02.09.2025