

Review of Artificial Intelligence Applications in Dams and Water Resources: Current Trends and Future Directions

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ARTICLE INFO	ABSTRACT
Article history: Received 27 November 2024 Received in revised form 26 February 2025 Accepted 7 March 2025 Available online 20 March 2025	This paper aims to analyze how AI can revolutionize dam and water resource management, the problem areas such as climate change, growing population rate, and deterioration of infrastructure; these AI technologies, in turn, drive predictive analytics, learning, real-time monitoring, decision-making, and resource management, thereby benefiting engineers and policymakers, among other stakeholders. Demand forecasting, flood management, and smart water quality monitoring enhance resource management, disaster prevention, and eco-conservation. On numerous occasions, AI models outcompete traditional hydrological approaches in terms of accurate water level and inflow predictions. In addition, the combination of AI with IoT sensors means that potential and actual conditions of dams and water quality are constantly monitored to optimize maintenance programs and avoid incidents. Problems arising from data quality and availability, interpretability of models, and the requirement of being a competent technical person hinder its widespread use. Similarly, ethical and legal considerations such as privacy and responsibility pose challenges to integrating AI into current systems. Addressing these challenges is very important if the impact of AI is to be enhanced. As highlighted in this analysis, there is a need for multi-disciplinary non-kingdom collaboration and specific expenditure to deal with these constraints. Each requires a greater research effort to improve our abilities to advance from non-parametric approaches to new paradigms of predictive modeling, big data, and real-time decision support and to become more responsible stewards of the Earth's limited water supplies. The outcomes highlight AI's potential to change water management and improve its effectiveness and sustainability. This research underscores the importance of ensuring a
real-time monitoring; data integration; climate adaptation	sustainable and secure water supply in the future to enable the provision of water supply as stipulated in the global sustainable environment and structures' agenda.

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1. Introduction

Dams are an important infrastructure for managing water resources for electricity generation, irrigation, flood control, aqua recreational activities, and water supply for domestic and industrial usage. Their locations and construction can effectively regulate local and even regional water availability, storage, and water-related ecosystem processes [1].

Dams also act as tanks where water can be stored for longer periods and made available during dry seasons. This is crucial, particularly for agriculture, where irrigation services are the key input in most producing areas [2]. Water availability is thus an important aspect of food security because of the role played by dams in regulating water supply [3]. Despite their benefits, managing dams and water resources presents several challenges: Climate change reduces water availability through a hiatus in rainfall, unpredictable monsoon rains, enhanced cyclones, floods, and severe droughts. It influences temperature regimes that affect water management [4]. It is stated that it affects the reliability and conservation of water and thus requires proactive management and use [5]. Several dams have deteriorating structural designs over time, thus necessitating construction works that would make them stronger and more efficient. Solving these problems may result in severe disasters and significant losses [6].

Although they can benefit ecosystems, dams create dangers, including interference with sediment or water flow movements and threats to migratory fish species. Sustainable dam management is the management of dams and the attendant water resources in a pro-human and pro-environment manner [7]. Problems become more complex because people multiply, and the need for water in our everyday lives grows. The abovementioned ways show how water resource management is required to develop effective resource-use strategies [8-10]. Artificial intelligence (AI) is a remarkable phenomenon that has affected most sectors today and will likely continue to do so. The use of this technology in dams and water resources management will likely have massive returns. The characteristics of the hydrological systems can explain the applicability of AI technologies in this area, the requirements for efficient resource management, and the need for advanced water management services [11-13].

In water resources, mechanical learning (ML) algorithms can process records to predict water supply and downs and optimize irrigation schedules. These algorithms can be masked and used to predict the patterns in the data on rainfall, reservoir levels, and, hence, the consumers' water intake [14,15]. Hydrology can also be understood with the help of big data and AI to analyze the large volume of data obtained from the sensors and satellite images and to assess the performance of the dam or look for the signs of water quality change and possible leakage or failure in the construction of the dam [16-18].

Al integration in technologies such as remote sensing allows tracking of water bodies, catchment areas, and watersheds over time [19]. This is beneficial in evaluating the suitability of the water resources, water quality, and the effects on the surrounding environment. For instance, computer analysis can successfully lead to the comprehension of changes in the water levels in the reservoirs or the density of vegetation around such reservoirs through satellite images [20]. Among the most common applications of advanced analytics, we can use it to predict floods or evaluate Dam health [6]. Al can use past climate conditions and engineering data to determine dam failure probability and the maintenance process based on weather conditions [21,22]. Al-based DSS can be applied by marrying several data sources and analytical techniques to aid water resource managers in determining the best strategies to assess water distribution, reservoir management, and hurricane response. These can also generate anticipated contexts to support tactics in strategic management [23].

Considering the increasing use of AI across several industries, a substantial gap persists in comprehensively comprehending and integrating AI-driven solutions for effective and sustainable dam and water resource management. Current research frequently emphasizes discrete AI applications, such as predictive water demand modeling or flood predictions, although it lacks a thorough synthesis that integrates these approaches' overall promise and constraints. This paper comprehensively examines AI applications in several aspects of water resource management, highlighting current accomplishments, problems, and prospects. The primary objective of this study is to address this knowledge deficiency by examining contemporary AI technologies, their deployment methodologies, and the related advantages and hazards. The aim is to educate and direct engineers, politicians, and academics on optimizing AI's influence in this vital domain. This study is essential due to the escalating demands of climate change, population expansion, and infrastructure degradation. It underscores the revolutionary capacity of AI to optimize water governance, augment predictive and real-time management, and guarantee sustainable and resilient practices that can protect water supplies for future generations. Figure 1 show the role AI applications in dams.

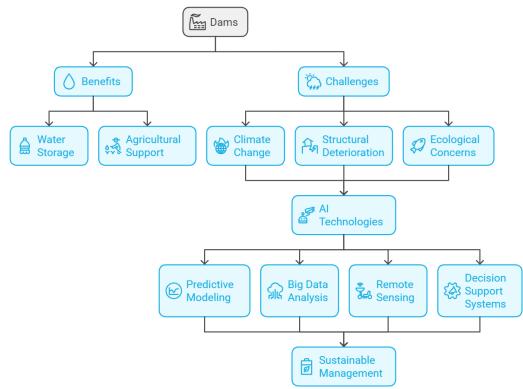


Fig. 1. AI applications in dams

2. Current Trends in AI Applications in Dams and Water Resources

2.1 Use of AI for Forecasting Water Levels, Inflow, and Demand

This paper analyses the use of AI algorithms in forecasting water levels, flow rates, and the need for water management, which has been deemed useful in contemporary society. Numerous studies have been reported probing the ability of AI techniques to provide good and sound forecasts. Figure 2 shows the VOSviewer map of a network of terminology associated with hydrology and water resource management. Three primary groupings emerge machine learning, hydrological modelling, and river-focused research. The map emphasizes the growing use of machine learning in hydrology,

the concentration on water dynamics and distribution, and the significance of river systems in hydrological research.

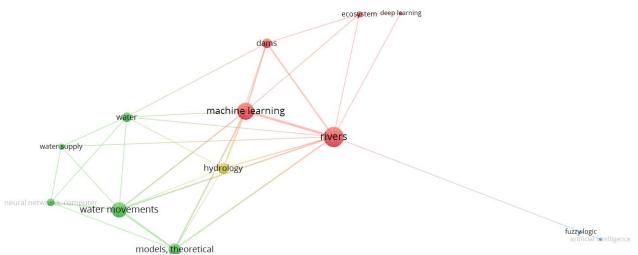


Fig. 2. A VOS viewer analysis of interdisciplinary connections in hydrological research

2.1.1 Forecasting water levels

It is worth emphasizing that, for some indicators, especially for water levels, machine learning algorithms have provided higher accuracy than hydrological models. For example, Park [24] employed ANN for the lake water level of the hydrological models. They also discovered that using the proposed ANN-based method will provide the upper hand and a higher level of accuracy compared to the simple linear regression underlying preparation and measurements of flood levels in advance. The water level prediction and forecasting always uses a Long Short-Term Memory (LSTM) model for predictions (Figure 3). This diagram depicts the essential elements of a gated neural network, commonly employed in architectures such as Long Short-Term Memory (LSTM) networks for processing sequential input. The architecture has three primary gates: Forget Gate (1), Input Gate (2), and Output Gate (3). The Forget Gate discards extraneous information from the prior state, ensuring the network concentrates solely on pertinent inputs. The Input Gate incorporates pertinent information into the current state, refreshing the memory content according to incoming input. The Output Gate disseminates the processed and updated information, regulating the information that advances via the network. This gated design enables the model to retain or discard information selectively, improving its capacity to grasp long-term relationships in time-series data or sequences.

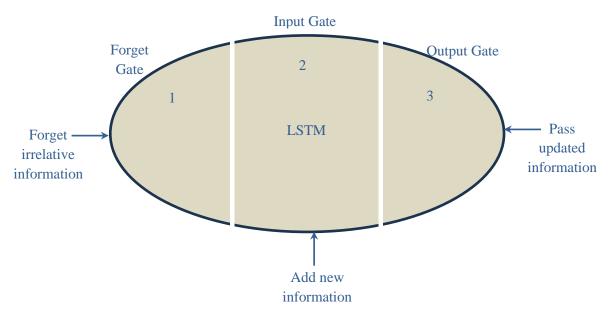


Fig. 3. Schematic representation of a gated neural network structure

2.1.2 Inflow predictions

AI models are also applied to estimate the inflow to the reservoirs and rivers using stream flow data, meteorological parameters, and knowledge of land use. For example, Özdoğan-Sarıkoç *et al.*, [25] only introduced the presence of the inflow in a reservoir and calibrated it with the same observed data using the base learning technique. The results will prove the possibility of using the developed AI models to refine the input for inflow forecasts regarding the reservoir operating rule and water resource management.

2.1.3 Water demand forecasting

Another sub-sector of water utility where authors found that AI has potential is predicting demand. Total water use can also be estimated using predictive total water use models incorporating a history of water use and other socio-economic, climatic, and demographic characteristics. In so doing, Kavya et al., [26] used a statistical technique called gradient boosting machines (GBM) to provide a good estimate of urban water demand. In regards to this study, the authors noted, while undertaking this work, that AI algorithms can identify new patterns of water consumption within society and, as such, play a role in the capacity of municipal authorities to make some changes in the utilization of available and usable water, according to findings by other investigators. Figure 4 demonstrates the utilization of machine learning, particularly neural networks, to forecast water flow within a hydrological system. The left side illustrates a basic model of a watershed, highlighting essential components such as precipitation, canopy interception, soil strata, and surface runoff. These pieces function as input data for the neural network. The network, seen by the linked circles on the right, processes the input data through many levels of nodes. The concealed layers discern intricate patterns and correlations among the data, and the output layer produces the ultimate water forecast. This methodology provides a robust instrument for comprehending and forecasting hydrological phenomena, facilitating enhanced water resource management and informed decisionmaking.

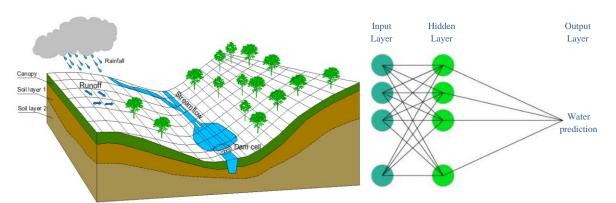


Fig. 4. A neural network model processes watershed inputs (rainfall, canopy, soil, runoff) to predict water flow

2.1.4 Integrated approach for enhanced accuracy

Also, using AI solutions in combination with the hydrological models yields additional improvement in terms of prediction. Tu *et al.*, [27] noted that advancing insights regarding the properties of water resource systems, the authors opted for applying machine learning concepts in hydrological modeling. Each of the works enhanced the precision of obtaining the water levels/inflow forecasts and demand with care using traditional methodologies of AI incorporation combined with hydrological knowledge.

2.2 Monitoring and Control Systems

This is due to the application of artificial intelligence (AI) to monitor the status of dam facilities and the quality of water being supplied in real time. Based on sophisticated analytical methods, these applications considerably improve the methodologies and processes for data acquisition, data analytics, and data interpretation pertinent to dam facilities and water quality processes and conditions.

2.2.1 Monitoring dam conditions

The predicted increased use of automated intelligent technologies, illustrated particularly by machine learning, is expected to be applied to ascertain the structural status and the state of the environment shared by dams. For example, while using the AI methods and the data of which strain gauges were achieved, Mata *et al.*, [28] established the state of the dam. They also noted that using machine learning algorithms makes it possible to use real-time data to predict future structural failures to enhance maintenance and risky rates. It allows the execution of measures that prevent failures that threaten nearby structures and populations. In the field of dam safety monitoring, several widely used machines learning methods, including Support Vector Machines (SVM) and Gaussian Process Regression (GPR), play significant roles.

(i) Support Vector Machines (SVM)

SVM is used in supervised learning techniques and is ideal for classification and regression activities, for it separates classes in the feature space by determining the optimal hyperplane. Application in dam safety concerning dam safety monitoring, SVM can be employed to identify the

status of the dam structures based on the features obtained from the sensors. For instance, it can assist in showing the condition of a particular structure, such as a dam, and whether it is stable or prone to collapse by analyzing fluctuations in the data on structural health and other influences. The algorithm of SVM is not very sensitive to overfitting, more so when it is used in high dimensional space and uses kernel functions to handle nonlinear relations.

(ii) Gaussian Process Regression (GPR)

GPR is a non-parametric Bayesian regression technique that provides a probabilistic approach to modeling data. This is based on the assumption that the data can be modeled through a Gaussian process, enabling quantification of the uncertainty for the predictions made. The application in dam safety is that GPR can be employed to estimate the future behavior of dam structures using past monitoring data. Be described by a Gaussian process, allowing for uncertainty quantification in predictions. The application in dam safety, GPR, can be utilized to predict the future behavior of dam structures based on historical monitoring data. It is especially valuable in determining the probability of structural abnormalities or failures because it supplies predictions and confidence intervals. GPR enjoys flexible modeling of the relationship under consideration and does not insist on any functional form of the relationship. Because it puts a numeric value to the degree of uncertainty, it is worth using to quantify risks in decision-making regarding dam safety.

2.2.2 Real-time water quality monitoring

Another important area where applications of AI are essential is real-time water quality monitoring. Smart sensors involve different data types, including temperature, turbidity, pH, and nutrient data. Given this, Razzano *et al.*, [29] described how these deep learning models can be utilized to analyze data collected by these sensors to accurately determine a well-being score and other water quality factors. It identified their work indicating how AI could be used in antiquity contamination surveys and some adequate, appropriate measures to protect the drinkability of water supplies. The proximity of AI in processing is more efficient in enhancing the reliability of the numerical water quality for assessment and in influencing interpositions of new contours.

2.2.3 Integration of IoT and AI for comprehensive monitoring

Other real-time possibilities for monitoring dam conditions and water quality using the IoT application in the AI application have also been improved. Smart monitoring systems employ the application of artificial intelligence concerning individual data flows from IoT devices, which makes it possible to monitor the conditions of water bodies and dams permanently. According to the authors Mishra *et al.*, [30], it enables improved monitoring by attending to the fact that the systems allow relating environmental conditions as experienced to the state of structures overall water resource management. The authors proved that this kind of analytics, based upon A, could be useful for explaining the impact of external circumstances, climate fluctuations concerning structure durability, and water purity.

2.2.4 Predictive maintenance through real-time data analysis

Just as with dam structures, through predictive maintenance, AI real-time monitoring is as useful in today's affairs as with civil arrangements. According to Yihong and Afzal [31], making specific

maintenance predictions using machine learning techniques to detect anomalies in historical or realtime sensor data is possible. From their studies, they discovered that it becomes quite feasible for managers to have more accurate timing through when the maintenance should be accomplished. Especially when it uses both predictive analysis and change monitoring, it is easier to improve the dependability and safety of the dams and improve the upkeep costs and their impacts on downtime.

3. Decision Support Systems

One of the main developments noted has been the application of artificial intelligence in the decision-making process on water resources, hence improving their quality and quantity management. Al, in particular, strengthens the decision support system (DSS) and enhances data processing to improve the engagement of the relevant stakeholders. Figure 5 also defines the concept of decision support systems (DSS) and how it relates to the individual and organization. DSS refers to computerized systems that aid in decision-making. They are model-driven, or, in other words, involve using mathematical models to analyze data to produce results. Both individuals and organizations can use DSS to improve decision quality and efficiency. DSS can help individuals make informed choices and organizations achieve their strategic goals by providing valuable information and support.

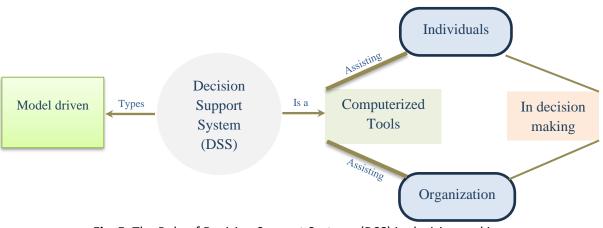


Fig. 5. The Role of Decision Support Systems (DSS) in decision making

3.1 Enhanced Decision Support Systems (DSS)

The decision support system has been enhanced with the help of AI technologies, as this approach provides the opportunity for a more detailed analysis of hydrological data. Parmar [32] has shown how AI can be embedded into DSS to support scenario-based assessment for water resource allocation decisions. Based on their recommendations, AI-integrated systems help decision-makers view further consequences of various management approaches under various environmental factors, thereby helping in thought-out executable strategic management. Using such algorithms, stakeholders can see several possible scenarios and improve decisions on the use of water and its conservation.

3.2 Predictive Analytics for Informed Decision-Making

AI-enabled predictive analytics has emerged as a core strategic resource for future water availability and demand forecasting. For example, Sousa *et al.*, [33] used ML to simulate water

demand in cities and evaluate the outcomes of the possible water conservation measures. For example, the study explained to the municipal planners how precious data can be leveraged in strategies that help enhance the smart distribution of water and reveal areas that need focus in water conservation for sustainability purposes. It helps the managers make necessary alterations according to some changes that are assumed to happen, giving the chance to apply correct corrections at the right time.

3.3 Stakeholder Engagement and Collaboration

Al is explicitly responsible for improving stakeholder engagement directly within frameworks involving water resources. With the help of Al in terms of visual analytics, problems concerning the management of water resources can be explained, and outcomes of possible actions can be visualized. Oyounalsoud *et al.*, [34] pointed out that Al-based tools enable collective decision-making by providing an interface with models and converting diverse, detailed narratives concerning water resources. Stakeholders involved are more trusting because all the parties can easily recall and envision the possible results of various decisions.

3.4 Adaptability to Changing Conditions

Since water resource decisions are made in dynamic contexts, decision-making procedures must be placed within an environmental philosophy that accommodates factors like climate change or other events like droughts and floods. The use of AI in these processes improves their flexibility and responsiveness. For example, Ghaffarian *et al.*, [35] examined the works that applied reinforcement learning for controlling water distribution systems and demonstrated how reinforcement learning could modify the control policies dynamically per the system's current state and environments. Their approach revealed that incorporating AI enhances flexible water management by making adjustments when new issues arise.

4. Risk Assessment and Management

It can be greatly noticed that the use of Artificial Intelligence (AI) in the evaluation of risks relating to the safety of dams and its effect on the environment has received much attention in the recent past. Such state-of-the-art approaches improve the swarm intelligence capability of engineers and water resource managers to forecast, supervise, and manage probable risks more efficiently. Figure 6 depicts a cohesive framework for risk management in water resource systems, consisting of three interconnected elements: Risk identification, risk evaluation, risk control, risk reduction, and risk dissemination. Risk Assessment is, therefore, a systematic technique of evaluating risks, threats, and impacts on a system using data and analytical estimates. Risk Management refers to risk management solutions based on mitigation, preparedness, response, and threat recognition policies that focus on sustainability and efficacy of decision-making. Risk communication is an exchange process that provides warning, assessment, and prediction, clarifying the understanding of risk to the interested parties. The cycle structure in the diagram, identified by arrows connecting every part, highlights that risk assessment, management, and communication are continuous and active processes to maintain the safety and sustainability of resources.



Fig. 6. Integrated framework for risk management in water resource systems

4.1 Risk Assessment for Dam Safety

Machine learning and data mining are popular artificial intelligence methods used to generate thorough risk analyses for the dam's safety. For example, Adamo et al., [36] used ANN in a case study for historical dam failure data analysis for future risk assessment of structural failure. The findings highlighted that AI models could help identify the potential level of dam failure and provide enhanced information to drive effective structural health monitoring and condition assessment practices and operational practices for reducing risks. The development of artificial intelligence (AI) and deep learning techniques, particularly in the context of underwater defect image processing and damage detection in concrete dams, is an emerging area of research that has significant implications for dam safety and maintenance. These technologies, including the YOLO (You Only Look Once) network, are state-of-the-art deep learning models designed for real-time object detection. It processes images in a single pass, making it highly efficient for detecting multiple objects within an image. In the context of concrete dams, the YOLO network can be trained to recognize various types of defects in underwater images. By using labeled datasets of defect images, the YOLO model can learn to identify cracks, corrosion, and other anomalies in real-time, facilitating timely maintenance actions. The realtime processing capability of YOLO allows for immediate analysis during inspections, enabling quick decision-making. Its high accuracy in detecting small and complex defects makes it particularly suitable for monitoring the structural integrity of dams. This application emphasizes the necessity of a model-based design to predict maintenance work and make the safety of the dams more efficient.

4.2 Environmental Impact Assessment

AI methods are also applied to evaluate the effects that occur during the operations and management of dams on the environment. Machine learning is an adept tool used to analyze the available environmental data, including water quality, habitat conditions, and some measures of biodiversity. When conducting their study, Aljohani *et al.*, [37] presented how random forest

classifiers can be applied to assess possible ecological consequences of dams. They opined that their work could determine the ecological thresholds that would help in understanding the future consequences of AI on the natural environment. This enables taking measures that will avoid adverse environmental effects while pursuing development.

4.3 Real-Time Monitoring and Anomaly Detection

As with the previous area, the AI techniques enable real-time monitoring and detection of deviations in dam safety and the environment. Automated detection based on the computations of progressive technology focuses on functionality variation from the normal range of values from sensors installed on the dam structures. The previous study conducted by Rajab *et al.*, [38] stated that implementing machine learning algorithms with IoT devices detected early signs of structural anomalies and hydrological change, which are fundamental signs of risk. Thanks to this capability, it is possible to intervene earlier when issues may be developing and dramatically enhance safety systems for dams and areas around them.

4.4 Simulation and Scenario Analysis

Al is also critical in modeling disaster possibilities about dams and environmental disasters. For example, Rehamnia *et al.*, [39] have used AI-based simulations to assess the consequences of dam failure on downstream populations and the environment. Their work showed that AI allows for the simulation of interactions within hydrological systems and facilitates fair evaluation of the results of various disaster response measures to address the identified impacts [23]. This predictive approach improves the existing disaster preparedness and response framework and offers useful information for practice. Table 1 summarizes the studies on AI Applications in dams and water resources.

The commonly used artificial intelligence models in the field of dams and water engineering can be summarized as follows:

- i. Artificial Neural Networks (ANN): ANNs are frequently employed for risk assessment and predictive modeling. They analyze historical data to predict future dam failures and assess structural health, as demonstrated by Adamo *et al.*, [36].
- ii. Random Forest Classifiers: This machine learning technique is utilized for environmental impact assessments, helping to evaluate the ecological consequences of dam operations by analyzing environmental data such as water quality and biodiversity.
- iii. Support Vector Machines (SVM): SVMs are often used for classification tasks in water resource management, including flood prediction and water quality assessment.
- iv. Decision Trees: These models help in making decisions based on various input parameters, useful in scenarios like water demand forecasting and resource allocation.
- v. Deep Learning Models: Advanced deep learning techniques are being explored for more complex predictive modeling, including hydrological modeling and real-time anomaly detection in dam safety.
- vi. Reinforcement Learning: This approach is being investigated for optimizing reservoir management and operational strategies by learning from the outcomes of past decisions.
- vii. Big Data Analytics: AI models that integrate big data analytics are crucial for processing large datasets from sensors and IoT devices, enhancing the monitoring and management of water resources.

These AI models collectively contribute to improved risk management, environmental assessments, real-time monitoring, and decision support systems in the context of dams and water resources.

Table 1

A summary of the studies related to AI Applications in da	ims and water resources
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AI Implementation	Description	Outcome/Benefit	Reference
Reservoir Management	AI algorithms optimizing reservoir	Improved flood control and	Özdoğan-Sarıkoç
Optimization	releases to balance supply and demand	water supply reliability	et al., [25]
Predictive Water	AI models predict future water	Optimized resource allocation	Kavya <i>et al.,</i> [26]
Demand Modeling	demand based on historical data and trends.	and reduced wastage	
Hydrological Modeling	Al-enhanced models predicting water flow and storage levels	Optimized reservoir operations and water allocation	Tu <i>et al.,</i> [27]
Real-time Monitoring Systems	Use of machine learning for continuous monitoring of dam conditions	Enhanced safety through early detection of structural issues	Mata <i>et al.,</i> [28]
Real-time Water Quality Monitoring	Al systems analyzing water samples for contaminants in real- time	Improved public health and regulatory compliance	Razzano <i>et al.,</i> [29
Structural Health Monitoring	Al-based data analysis from sensors to assess structural integrity	Proactive maintenance scheduling and risk mitigation	Mishra <i>et al.,</i> [30]
Predictive Maintenance	Predictive analytics to schedule maintenance based on wear and tear	Reduced downtime and costs associated with maintenance	Yihong and Afzal [31]
Integrated Water Resource Management	Al systems integrating various data sources for holistic water management	Enhanced decision-making and policy formulation	Parmar [32]
Water Loss Detection	Machine learning applications identifying leaks in distribution systems	Reduced operational costs and enhanced service reliability	Sousa <i>et al.,</i> [33]
Drought Monitoring and Prediction	Al tools analyzing climate data to predict drought conditions	Improved preparedness and resource management strategies	Oyounalsoud <i>et</i> <i>al.,</i> [34]
AI in Emergency Response Planning	Simulation models that incorporate AI to evaluate emergency responses	Improved preparedness for dam failure scenarios	Ghaffarian <i>et al.,</i> [35]
Dam Safety Assessment	Image processing and machine learning to assess dam conditions from aerial imagery	Identified maintenance needs quickly and accurately.	Adamo <i>et al.,</i> [36]
Flood Forecasting Models	Al models that analyze weather patterns to predict floods	Improved flood response and management strategies	Aljohani <i>et al.,</i> [37
Flood Prediction and Management	Machine learning algorithms assessing weather patterns for flood forecasting	Enhanced emergency response and infrastructure protection	Rajab <i>et al.,</i> [38]
Seepage Detection Algorithms	Machine learning algorithms to identify seepage through data analysis	Prevention of potential water loss and structural damage	Rehamnia <i>et al.,</i> [39]

5. Challenges and Limitations of AI Applications in Dams and Water Resources

Subsequently, this research identifies the following challenges and limitations in the application of AI solutions for managing dams and water resources while outlining the nevertheless great potential of these technologies:

5.1 Data Quality and Availability

The current use of AI applications in dams and water resources has limited weaknesses, with a crucial concern for data quality and available data. The studied problem has several limitations: First, some of the gauged watersheds need complete water use records, preventing or hindering machine learning models' training and subsequent decision-making [40,41]. The application of AI and the current structures also face technical challenges, such as requiring new and better sensors and data-gathering mechanisms, which can be expensive and inaccessible [13,42].

Uncertainty in water quality data arises from various environmental aspects, causing inconsistencies in AI outcomes and conclusions [43,44]. In addition, depending on historical data to train the artificial intelligence may be an issue because what worked yesterday may be a different topic today depending on the region or province, company, city, or country [45]. The environment is changing very fast, or floods, droughts, storms, hurricanes, and all other calamities may occur more frequently than before. Finally, concerns related to data protection and the possibility of bias incorporated into algorithms remain issues when introducing AI technologies into the water management area. Table 2 summarizes of the studies that are related challenges and limitations in data quality and availability.

Table 2

Summarizes of the studies that are related challenges and limitations in data quality and availability

Authors and year	Challenge/Limitation	Description
Konya and Nematzadeh [40],	Inconsistent Data	Inconsistency and incompleteness of water-use
Marston <i>et al.,</i> [41]		data hinder effective AI model training.
Jenny <i>et al.,</i> [13],	Technical Barriers	Integration of AI with existing infrastructure faces
Hariri-Ardebili <i>et al.,</i> [42]		technical challenges and high costs.
Carvalho <i>et al.,</i> [43],	Variability in Water	Environmental factors lead to inaccuracies in AI
Chen <i>et al.,</i> [44]	Quality Data	predictions due to variable water quality data.
Ho and Goethals [45]	Historical Data Reliance	Rapid environmental changes may not be
		reflected in historical datasets used for AI training

5.2 Interpretability and Transparency

Another problem is the over-parametrization of models, especially deep learning algorithms ones; the resulting models act like 'black boxes,' which does not allow practitioners to have any insights into how conclusions are arrived at. A lack of openness could harm the credibility of such decisions among engineers and policymakers, and these two entities need clear explanations of AI-generated forecasts and proposals [46]. However, a major concern is the application of artificial intelligence into traditional water management systems, where data quality and availability issues are likely to impact the reliability of the designed models. Additionally, AI (XAI) frameworks are required since such approaches can explain model actions and increase users' trust in them. However, establishing good XAI techniques remains challenging because such techniques have to balance interpretability and accuracy. Finally, issues such as bias in data and the impact of having an

automated decision process raise great ethical dilemmas that make applying AI in this field even more challenging [47].

5.3 Technical Expertise and Capacity

Al applications in dams and water resources are currently experiencing several challenges and limitations, mainly in the technical expertise and capacity. Perhaps the most acute problem is the shortage of professional employees who would be able to apply and supervise AI solutions in the sphere of water management. Hydrology or AI specialists are often hard to come by, and many organizations fail to implement these emerging technologies effectively. Moreover, implementing AI into current water management practices usually entails significant costs associated with improving physical infrastructure and employee training, which is not easily feasible for most water utilities, especially those in the developing world [48].

5.4 Ethical and Legal Considerations

Simply employing AI in water management has certain ethical and legal risks. Privacy and security concerns are important when a body obtains, stores, or analyzes personal information within the community water systems. Moreover, using AI to make decisions raises concerns about who is to blame when decisions made with the assistance of artificial intelligence led to adverse outcomes [49].

Ethical issues involve data ownership, responsibility, and fairness while using AI solutions. Additionally, given the immense computing requirements of some AI applications, AI accessibility can be restrained by permutations of economic and infrastructural constraints inherent with petite organizations or even geographic locations with substandard technical amenities [50]. Such issues serve to highlight the fact that more holistic approaches are needed in order to gain an understanding of how Artificial Intelligence tools and techniques should best be employed in water resource management now and in the future, as well as the most important technical, ethical, and legal questions that should be asked and answered. Solving these ethical issues is crucial for building the public's trust in the technologies that apply AI [51].

5.5 Integration with Existing Systems

One of the main challenges of AI applications for water management is the compatibility of the AI with existing systems and installations. They may not be compatible with other newer AI technologies; this becomes a challenge during implementation. However, the continuous upgrade and maintenance of the developed techniques act as a challenge since it may lead to additional logistics demands where organizations undertaking AI implementation have to consider finances and other types of resources that they need to allocate to continually update and maintain their AI methods [52]. This integration challenge requires time and effort to avoid hitches during its operation and maximize its efficiency. Figure 7 summarizes the challenges and limitations of AI applications in dams and water resources.

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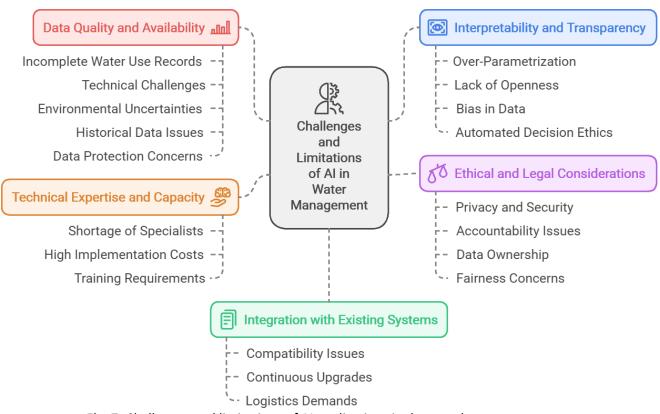


Fig. 7. Challenges and limitations of AI applications in dams and water resources

6. Future Directions of AI Applications in Dams and Water Resources

As water resource management continues to advance as a discipline, using Artificial Intelligence (AI) offers countless prospects for improving key structures, primarily the dams and water resources. Future directions for AI applications can be explored in several critical areas:

6.1 Enhanced Predictive Modeling

Newer evolutions of future AI will use superior stochastic models and sophisticated replicational methods to create multiple hydrological models. Further developing and implementing superior machine learning classifiers, including ensemble and deep learning, may enhance the forecasts concerning water availability, floods, and demand [53]. To create such models, further integration with higher-quality datasets that capture near-real-time changes in hydrological states and hydrodynamic processes will be necessary, improving future forecasting and planning.

Also, AI can help monitor and control water usage in real-time to ensure immediate actions are taken to prevent floods or water shortage events. This capability is critical to the structural integrity and reliability of dams and water supply; hence, it should be a priority. Therefore, AI integration in smart water management systems also contributes to the development of sustainable practices in water usage and waste minimization [54].

6.2 Big Data Integration

The future direction of AI applications in dams and water resources will help improve infrastructure's operational efficiency and safety, besides the function of big data together with advanced machine learning techniques. AI can support preventative and monitoring of the state of the structures through information gathered from sensors and SAT images, among others. Big Data analytics ensures that large pieces of information can be processed, which makes it easier to get accurate estimates of water inflows and reservoirs, which are essential for water resources management. Moreover, AI-enabled models can potentially provide solutions for the dyke system and estimate the consequences of climate change and extreme weather conditions for dam operation. IoT technologies supplement data acquisition and monitoring, giving a complete picture of dams and their environment [55,56]. The subsequent research trends will probably be directed toward enhancing the AI algorithms used to introduce uncertainty quantification and enhance the decision-making concerning the dam.

6.3 AI-Driven Decision Support Systems

The future direction of AI applications in dams and water resources is planned to improve the decision-making system and operation. Artificial intelligence and decision support systems (DSS) are becoming more popular with applications in water resource management (WRM) in several areas, such as demand for water, water treatment, and disaster management. Such systems involve large amounts of data like weather data and soil moisture, thus giving valuable information that can enhance efficient water supply.

As for the future development of AI applications in dams and water resources, its purpose will enhance the decision-making system and operation.

Artificial intelligence and decision support systems (DSS) are being adopted to increase measures for use in water resource management (WRM) in many areas, including water demand, water treatment, and disaster management. Such systems involve massive amounts of weather data and soil moisture, thus providing useful information that can improve the sustainable practices.

The possibilities of using AI in this sphere are also connected with increasing the readiness of the community to face climate-related challenges through better utilization of resources and the elaboration of optimized strategies in case of emergencies. Over time, the issues are likely to change, with the application of more complex models for mimicking a wide range of situations and identifying strategies for the future development of existing and new infrastructure [57].

6.4 Focus on Sustainability and Resilience

The future directions of AI in dams and water resources are pointed out as improvements in sustainable utilization and resilience. AI technologies are being used to utilize the WRM by applying big data analytics, including climate data, water quality data, and water consumption pattern data. It means that actual monitoring and predictive analysis can be carried out so that decisions can be made in advance regarding water deficit and other environmental problems.

In addition, AI applications are preeminent for efficient precision agriculture, which, in turn, helps conserve water resources for irrigation and provide food security and sustainability. This means that more advanced structures of AI systems will start being developed to consider the changing environment and assist water resource sustainability in the long run [58].

6.5 Improved Stakeholder Engagement

Future studies also need to examine how AI implementation could help improve stakeholders' engagement and participatory decision-making systems more effectively. When water managers, communities, and policymakers collaborate on AI-based platforms, improved water governance will

enable inclusive outcomes for greater populations. In future directions, it is possible to identify methods based on natural language processing, sentiment analysis, etc., to help manage stakeholders' needs and concerns more adequately [59-61]. Figure 8 summarizes the future directions of AI applications in dams and water resources.

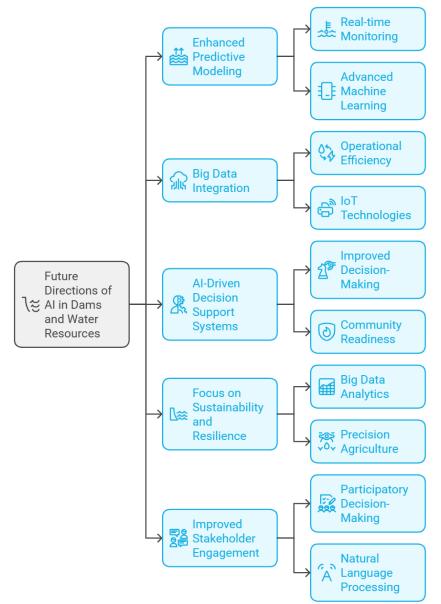


Fig. 8. Future directions of AI applications in dams and water resources

7. Conclusions

Al in dam and water resource management represents the change needed to address contemporary challenges, including global warming, water scarcity, and structural vulnerabilities. In the context of the increasing application of artificial intelligence, industry specialists might enhance the effectiveness of prognostics, constant tracking, and decision-making. Artificial intelligence-based technology solutions, such as water demand forecast, flood risk, and water quality analysis, have contributed to improved resource utilization and risk management. These advancements demonstrate that Al can be considered an eco-disruptive technology that can lead to sustainable

water management and water infrastructure that can quickly adapt to changes in environmental conditions.

However, the practical application of AI technology requires certain complexities. Other limitations in the use and analysis of data remain significant challenges, with data quality and accessibility remaining significant problems, especially in regions where the basic technological framework is relatively poor. Some AI models remain complicated for customers, investors, and institutions, whose goals are clear and easily understandable interpretations of the decision-making process. There is a need for more qualified personnel, and some concerns are emerging regarding the ethical and legal use of AI, such as questions about data ownership and accountability, stopping significant adoption. Addressing these limits requires rigorous approaches, including data infrastructure, building explainable AI, and developing interdisciplinary professionalism.

The future of AI in water resource management will be contingent on groundbreaking advancements and partnership endeavors. The application of high-quality data and Big Data Integration in advanced predictive modeling shall increase forecast accuracy and decision-making capability. Decision support systems under the AI paradigm should be designed to be as flexible as possible, integrate multiple stakeholders, and promote a culture of transparent governance. The applications of Artificial Intelligence should include ecological and hydrological data to focus on sustainability and environmental responsibility. Proper implementation of AI depends upon cooperation between politicians, engineers, researchers, and local communities. Maintaining the idea of innovation and incorporating the concept of inclusion forms the new sustainable stream of water supplies that meet the demands of the present and future generations.

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Conflicts of Interest

The authors declare no conflict of interest.

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