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Artificial Intelligence for Sustainable Water Resource Management: Opportunities, Challenges, and Future Directions

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Abstract

Global water resources face unprecedented stress from climate variability, population growth, and urbanisation, exposing the limitations of traditional, deterministic management approaches. Artificial intelligence has emerged as a disruptive paradigm for bridging the aforementioned operational gaps through advanced predictions, real-time monitoring, and system optimisation. This study conducted a qualitative systematic literature review of peer-reviewed research published between 2005 and 2026 to evaluate the integration of AI within sustainable water governance.

The literature synthesis of this study indicated that while machine learning and deep learning have enhanced short-term water demand forecasting and predictive maintenance, recent developments focus on regional water consumption modeling and AI applications for pollutant detection. However, challenges remain, including the opacity of AI models, geographic biases favouring developed regions, and a disconnect between AI outputs and institutional decision-making process.

This study concluded that the future maturity of digital water systems depends on a shift from purely technical performance to explainable AI, digital twins, and algorithmic auditing frameworks. Ultimately, AI can advance United Nations sixth Sustainable Development Goal only when it is seamlessly integrated with collaborative, equitable governance and evidence-based policy structures.

Keywords: *artificial intelligence, machine learning, policy integration, sustainable water governance, water resource management*

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1. Introduction

Water stands as the foundational cornerstone sustaining human health, macroeconomic development, agricultural security, and global ecosystem stability. However, the compounding pressures of accelerated climate variability, demographic growth, rapid urbanisation, and industrial pollution have pushed global water security to a critical threshold (Sun & Scanlon, 2019; Silva, 2026; Richards et al., 2023). Traditional water resource management frameworks have historically relied on static, deterministic hydrological models and highly localised, manual decision-making processes (Sliva, 2026). In today's dynamic environmental landscape, the previously mentioned conventional paradigms increasingly struggle to accommodate the randomness, nonlinear complexities, and deep uncertainties associated with modern hydroclimatic disruptions (Mineo et al., 2022; Ghobadi & Kang, 2023).

Concurrently, the rapid evolution of Artificial Intelligence (AI) has become a disruptive technological boundary that is claimed to transform contemporary water governance (Batarseh et al., 2023; Krishnan et al., 2022). By leveraging machine learning (ML), deep learning (DL), and the Artificial Intelligence of Things (AIoT), modern systems can consume massive environmental datasets, uncover latent hydrological patterns, and generate high-fidelity predictive insights (Rahman et al, 2026; Bagheri et al., 2023).

Academic interest has grown in the deployment of AI for short-term urban water demand forecasting, localised water quality monitoring, and predictive utility maintenance (Herrera et al., 2019; Shan et al., 2023; Murray et al., 2025), which includes advances in machine learning frameworks, neural networks, and explainable AI approaches that improve both prediction accuracy and interpretability in water systems (Williams, 2009; Paneru & Paneru, 2024; Malisaba et al., 2026).

Despite the previously mentioned technical milestones, the operational reality of AI in water resource management remains highly fragmented. A significant portion of current scholarship focuses on isolated technical performance metrics, leaving a critical knowledge gap regarding how the earlier-mentioned advanced tools can be systematically integrated into broader public policy, regulatory compliance frameworks, and long-term climate adaptation strategies (Mineo et al., 2022; Wang et al., 2025;

Poudel, 2026). Consequently, a rigorous macro-level evaluation is required to assess how AI can transition from a purely computational mechanism into an instrument of strategic, sustainable water governance (El-Dakhakhni et al., 2025; Fraternali et al., 2012).

The core challenge in contemporary water management lies in balancing competing human, agricultural, and ecological water demands against a backdrop of severe, climate-driven resource constraints. Traditional linear decision-making tools lack the predictive agility and computational scalability necessary to navigate highly volatile environments. While advanced AI applications offer viable solutions to these modeling limitations, their widespread institutional adoption is fundamentally obstructed by three systemic blockages: high-performing deep learning models are inherently hard to understand, exhibiting severe deficits in transparency, interpretability, and explainability (Otamendi et al., 2024). This "black-box" nature fundamentally undermines stakeholder trust and creates accountability risks for public utility managers who must validate algorithmic recommendations before execution.

The current body of literature exhibits a severe geographic bias, with empirical testing overwhelmingly concentrated in data-rich, developed nations. Consequently, there is a profound lack of understanding of the operational barriers, sensor calibration limitations, and contextual constraints to deploying AI in data-scarce, infrastructure poor developing regions, the very areas suffering the highest climate vulnerabilities (Krishnan et al., 2022).

There is an acute disconnection between advanced computational AI frameworks and actual regulatory water governance. Current research prioritizes micro-level technical optimization while neglecting the institutional architectures, algorithmic auditing standards, and policy mechanisms required to translate AI outputs into equitable, evidence-based water regulations (Omar et al., 2023).

Without resolving the above mentioned problems including interconnected technical, geographical, and institutional tensions, the potential of AI will remain trapped within theoretical computational spaces rather than advancing the United Nations Sustainable Development Goal six. Based on the research problem research questions are considered: which core computational paradigms, specifically within machine learning, deep learning, and AIoT sensor networks, are most prominently deployed in the current water resource management literature?; how effectively do AI-driven systems improve predictive accuracy and longitudinal scaling across the domains of regional water consumption estimation, real-time pollution surveillance, and long-term climate risk mitigation?; what specific data dependencies, algorithmic opacity risks, geographic biases, and ethical constraints restrict the systemic implementation of AI by water utility planning authorities and regulatory bodies?, and how can emerging technologies like Explainable AI (XAI) and digital water systems be systematically operationalised to facilitate collaborative, climate-resilient water governance and evidence-based policymaking?

The broad objective of this study is to execute a qualitative systematic literature review to critically evaluate the strategic role, systemic limitations, and governance implications of integrating Artificial Intelligence into sustainable water resource management frameworks.

The specific objective of this study are: to identify and classify the dominant AI, machine learning, and AIoT architectures applied across contemporary water resource engineering applications; to evaluate the operational performance, scope expansion, and predictive capabilities of AI within water demand forecasting, real-time quality monitoring, and climate resilience planning; to critically analyse the primary socio-technical, ethical, and structural barriers hindering the mainstream institutional adoption of AI-driven water systems, and to establish a conceptual blueprint mapping future research direction, focusing on Explainable AI (XAI), digital twin frameworks, and the integration of AI models into public policy and water regulations.

This study synthesised the interactions between computational data science and environmental engineering, focusing on the applications of neural networks and digital water frameworks that enhance theoretical understanding of environmental analytics by integrating diverse findings and emphasising the role of machine learning in addressing long-term climate and sustainability challenges. For practitioners in water utilities and infrastructure, the research offers a diagnostic roadmap to optimise operations by addressing the limitations of predictive analytics, including data dependence and model opacity. This study also bridges the gap between technical AI capabilities and policymaking, guiding environmental agencies and policymakers on integrating AIoT monitoring and explainable AI into regulations. Furthermore, this study also exposes geographic biases in AI testing, addresses barriers faced by developing nations, and provides a framework for connecting water distribution systems to the United Nations Sustainable Development Goal six for equitable climate resilience.

2. Literature review

Concept of AI in water management

Artificial Intelligence refers to computational systems capable of performing tasks that typically require human intelligence, including learning, reasoning, prediction, and decision-making. In water management, AI enables automated analysis of large environmental datasets and supports intelligent decision-making processes (Batarseh et al., 2023).

Machine Learning applications

Artificial Neural Networks (ANNs) have been widely used in water resources research since the early 2000s (Tanty & Desmukh, 2015). Das and Rad (2020) demonstrated that ANNs can effectively model complex hydrological processes. Similarly, Williams (2009) highlighted the growing importance of neural-network-based approaches in water resource prediction and management. ML techniques such as Random Forests, Support Vector Machines (SVMs), and gradient boosting have significantly improved predictive performance in water-related applications (Mineo et al., 2022).

Water demand forecasting

Accurate water demand forecasting is critical for sustainable resource allocation. Herrera et al. (2019) demonstrated the effectiveness of ML approaches in predicting urban water demand. Shan et al. (2023) further developed an Attention-BiLSTM model integrated with XGBoost residual correction, achieving high forecasting accuracy and stability in short-term water demand prediction.

Recent studies of Shan et al. (2023) further demonstrate the growing effectiveness of AI in water consumption forecasting and demand estimation. Alzraiee et al. (2024) developed an ML framework for estimating public water withdrawals across the United States, incorporating hydroclimatic, demographic, socio-economic, and land-use variables. Their findings revealed substantial longitudinal and seasonal variability in water demand (Mahmoud et al., 2023).

They also demonstrated the capability of AI models to support future water-demand forecasting under different climate and population-growth scenarios. Similarly, Murray et al. (2025) applied machine learning techniques to estimate domestic water use from public and private water sources, providing more accurate assessments to support sustainable water planning and resource allocation.

Water quality monitoring and environmental management

AI technologies increasingly support water quality assessment and pollution monitoring. Bagheri et al. (2023) emphasised the role of deep learning and Tiny Machine Learning (TinyML) systems in real-time environmental monitoring. They further suggest that AI-based monitoring systems can provide low-cost and autonomous solutions for pollutant detection.

Similarly, recent studies by Zou et al. (2025) have highlighted the importance of AI in detecting contamination patterns, assessing ecosystem health, and supporting environmental sustainability.

The emergence of AIoT technologies has further enhanced environmental monitoring capabilities. Rahman et al. (2026) reported that AIoT-enabled water quality management systems integrate sensors, machine learning algorithms, and real-time analytics to improve contamination detection, resource monitoring, and operational decision-making, which facilitates continuous monitoring while reducing operational costs and increasing responsiveness to environmental changes.

Smart water management systems

Smart water systems integrate sensors, IoT devices, and AI algorithms to optimise water distribution and infrastructure operations. Recent reviews indicate that AI-driven smart water management systems enhance operational efficiency, reduce water losses, and improve decision-making capabilities (Omar et al., 2023).

Water scarcity is increasingly recognised as one of the most pressing global sustainability challenges. Recent research demonstrates that AI can support water harvesting, drought mitigation, and climate adaptation strategies. Benitez and Singh (2025) found that AI-based optimization models improve rainwater harvesting systems, increase water-use efficiency, and strengthen urban resilience to water shortages. Likewise, Silva (2026) highlighted the role of AI in promoting sustainable water resource management through intelligent allocation strategies, predictive analytics, and resource optimisation, indicating that AI can contribute significantly to achieving Sustainable Development Goal six by enhancing water security under changing climatic conditions.

Synthesis of the literature

The literature consistently identifies Artificial Neural Networks (ANNs), Machine Learning (ML), Deep Learning (DL), Random Forests (RF), Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, Explainable AI (XAI), and AIoT systems as the most widely applied technologies in water resource management (Ghobadi & Kang, 2023; Krishnan et al., 2022; Rahman et al., 2026), which are used for forecasting, optimisation, classification, and real-time monitoring.

Studies demonstrate that AI significantly improves water demand forecasting through advanced predictive analytics and neural-network-based models (Morain et al., 2024; El-Dakhakhni et al., 2025). AI is also widely used in water quality monitoring through AIoT sensors, deep learning, and explainable AI frameworks, which facilitate real-time assessment and anomaly detection (Rahman et al., 2026; Paneru & Paneru, 2024). Sustainability applications include smart water distribution, basin management, drought prediction, and resource optimisation.

Benefits identified across studies include improved prediction accuracy, real-time monitoring, efficient resource allocation, leak detection, reduced water losses, and enhanced decision-making capabilities (Silva, 2026; El-Dakhakhni et al., 2025). However, limitations include data scarcity, model opacity, high implementation costs, sensor calibration issues, limited generalisability, and concerns about trustworthiness (Rahman et al., 2026; Xia et al., 2025).

Recent studies emphasise the need for explainable AI (XAI), trustworthy AI systems, digital twins, federated learning, scalable AI frameworks, interdisciplinary collaboration, and broader adoption in developing countries (Rahman et al., 2026; Xia et al., 2025; Silva, 2026). Researchers also recommend integrating AI outputs into policymaking and governance frameworks to support sustainable water management.

Research gap

Despite advancements in AI for water resource management, significant research gaps persist. Firstly, existing studies often focus on specific applications such as water demand forecasting or flood prediction, neglecting the holistic integration of AI into broader water governance frameworks. For instance, research by Ghobadi and Kang (2023) and Morain et al. (2024) highlights the technical performance of machine learning. However, it lacks exploration of AI's role in institutional coordination and stakeholder involvement, both of which are crucial for integrated water resource management (IWRM).

Secondly, there is limited investigation into the long-term sustainability impacts of AI in this field. While studies demonstrate improved forecasting and operational efficiency (El-Dakhakhni et al., 2025; Silva, 2026), they often do so over short periods and place little emphasis on the broader environmental, economic, and social implications of AI adoption, leaving questions about its long-term viability amid changing climatic conditions.

Additionally, the explainability, transparency, and trustworthiness of AI models are under-addressed. Many sophisticated models function as "black boxes," yielding accurate predictions without clear explanations, which can undermine stakeholder trust and complicate decision-making processes despite recent calls for Explainable Artificial Intelligence (XAI) in water management (Paneru & Paneru, 2024; Xia et al., 2025).

Moreover, most research exhibits geographic bias, with AI applications predominantly tested in developed countries, overlooking the unique challenges faced by developing nations, which suffer from water scarcity, inadequate infrastructure, and climate-related vulnerabilities (Rahman et al., 2026). This results in an insufficient understanding of the barriers and contextual factors that influence AI implementation in low- and middle-income settings.

Lastly, there is a notable disconnection between AI systems and policy decision-making. Current literature emphasises the technical aspects of AI while neglecting how insights derived from AI could enhance water policies and governance structures. Effective water management requires collaboration among stakeholders, yet the existing body of work offers limited guidance on how AI can facilitate evidence-based policymaking and improve transparency in governance processes. Addressing these gaps is vital for translating technological innovations into practical and sustainable water management solutions.

Another emerging research gap concerns the governance and regulatory implications of AI in water management. While technical applications continue to expand, research on how AI can support regulatory compliance, policy implementation, and institutional decision-making remains limited. Wang et al. (2025) identified a growing need for AI-assisted policy analysis and regulatory monitoring to improve the effectiveness of water governance. Furthermore, Poudel (2026) highlighted concerns regarding the reliability and accountability of AI-generated recommendations in water utility planning, emphasising the importance of auditing and validating AI-supported decisions before implementation.

3. Methodology

This study applied a qualitative systematic literature review (SLR) to investigate the integration of AI in sustainable water resource management. This method was chosen for its ability to thoroughly identify and evaluate evidence on the topic while minimising bias. Given the interdisciplinary nature of AI-enabled water management, which spans environmental science, hydrology, engineering, sustainability, and computer science, a systematic approach was fitting (Ghobadi & Kang, 2023; El-Dakhakhni et al., 2025).

The review examined peer-reviewed articles published between 2005 and 2026, sourced from academic databases such as Web of Science, Scopus, and ScienceDirect. It focused on recent studies concerning water demand forecasting, consumption assessment, quality monitoring, and climate resilience. Emerging topics included Explainable AI (XAI), Artificial Intelligence of Things (AIoT), and AI-supported policy development (Murray et al., 2025).

Studies were selected based on criteria emphasising AI techniques relevant to water management, including machine learning and deep learning. Data extraction was systematically conducted, capturing key information on publication year, objectives, AI applications, findings, and future recommendations. Noteworthy examples highlighted the effectiveness of machine learning in estimating water withdrawals and forecasting domestic water use, as well as AI's role in optimising water systems and resource allocation (Rahman et al., 2026; Wang et al., 2025).

The literature was analysed using thematic content analysis, which revealed six categories: forecasting water demand and consumption, quality monitoring, drought prediction, smart infrastructure management, water scarcity and sustainability, and governance support. This underscores the evolving role of AI in both technical operations and strategic planning (Alzraiee et al., 2024; Richards et al., 2023; Wang et al., 2025).

To validate the review, selected studies were critically assessed for methodological quality and relevance to sustainable water management. Emphasis was placed on high-quality recent research addressing explainability, ethical implementation, and governance. The methodology enabled a comprehensive synthesis of AI applications in water resource management, highlighting opportunities and challenges and suggesting future directions in addressing environmental and societal pressures (Benitez & Singh, 2025; Silva, 2026; Xia et al., 2025; Paneru & Paneru, 2024; Villarin & Rodriguez-Galiano, 2019).

4. Results

The systematic review of selected studies reveals that AI plays a role in many different aspects of sustainable water resource management. The findings are organised into six major thematic application areas, integrating both traditional water management functions and emerging research directions identified in the additional datasets.

Water demand and consumption forecasting

The reviewed studies consistently demonstrate that AI significantly improves the accuracy of water demand forecasting compared to conventional statistical and deterministic methods. ML, DL, and hybrid architectures such as Attention-BiLSTM combined with XGBoost show superior performance in capturing nonlinear consumption patterns.

Recent evidence from extended datasets highlights a shift from short-term forecasting to large-scale water consumption estimation and modeling. AI models incorporating hydroclimatic, demographic, socio-economic, and land-use variables are increasingly used to predict regional and national water withdrawal patterns, which enable more robust planning under conditions of climate uncertainty, population growth, and urban expansion (Batarseh et a., 2023).

Furthermore, AI-based approaches provide more accurate estimates of domestic water use from both public and private sources, offering higher precision than traditional survey-based methods. This enhances long-term water allocation planning and supports sustainable consumption management.

Water quality monitoring and environmental assessment

AI-based systems demonstrate strong capability in real-time water quality monitoring and environmental assessment. Deep learning models and AIoT-enabled sensor networks effectively detect pollutants, classify contamination patterns, and monitor ecological health conditions.

The integration of Tiny Machine Learning (TinyML) enables low-cost, edge-based water monitoring systems that operate without continuous cloud connectivity. This improves scalability in resource-constrained regions. The results indicate that AI significantly enhances early warning systems for contamination events and supports continuous environmental surveillance.

Drought prediction and climate resilience

The findings show that AI plays a critical role in drought prediction, climate risk assessment, and hydrological forecasting. Machine learning models trained on large-scale meteorological and hydrological datasets improve early detection of drought conditions and support proactive water management strategies. Recent findings emphasise AI's role in climate resilience and adaptation planning. AI-driven models support scenario-based forecasting, enabling water managers to simulate future water availability under different climate-change scenarios. This enhances preparedness for extreme weather events and long-term hydrological variability.

Smart water infrastructure and operational efficiency

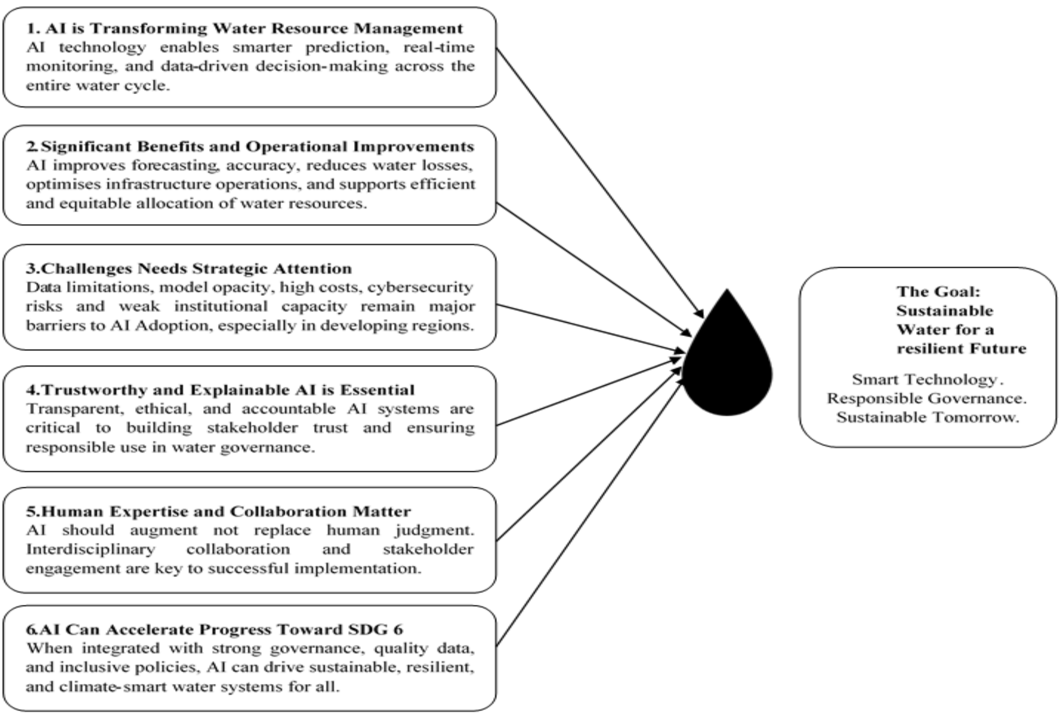
AI-enabled smart water systems integrate IoT sensors, predictive analytics, and optimisation algorithms to improve infrastructure performance. The results indicate significant improvements in Leakage detection, and reduction plays a critical role in improving the efficiency of water supply systems by identifying and addressing hidden losses in pipelines before they escalate. In addition, predictive maintenance of pipelines, supported by data-driven monitoring and analytics, helps anticipate failures and schedule timely repairs, thereby reducing unexpected breakdowns and service interruptions.

Optimisation of distribution networks further enhances system performance by improving pressure management, flow control, and water routing, ensuring equitable and efficient delivery across service areas. Together, these strategies significantly reduce non-revenue water losses by minimising physical leakage, operational inefficiencies, and unauthorized consumption, ultimately strengthening the financial sustainability and reliability of water utilities. The above-mentioned systems enhance operational efficiency and reduce water wastage, particularly in urban water supply systems. AI-based infrastructure monitoring also enables real-time decision-making and improves system reliability.

Summary of the results

Figure 1

Summary of the results



Consistent with Batarseh et al. (2023), AI technologies significantly improve forecasting accuracy, water quality monitoring, infrastructure optimisation, and decision support. The reviewed studies collectively indicate that machine learning and deep learning models outperform many traditional statistical approaches in addressing complex, nonlinear, and data-intensive water management problems.

Recent evidence from studies on future water consumption further reinforces the strategic importance of AI. Alzraiee et al. (2024) demonstrated that machine-

5. Discussion

The findings of this review demonstrate that Artificial Intelligence (AI) is increasingly becoming a critical tool for sustainable water resource management.

learning models can effectively estimate public water withdrawals by integrating hydroclimatic, socio-economic, demographic, and land-use variables. Their findings suggest that AI can support proactive planning under conditions of climate uncertainty and population growth. Similarly, Murray et al. (2025) found that AI-based estimation methods provide more accurate assessments of domestic water use than conventional approaches, thereby enabling more efficient allocation of water resources. The above-mentioned findings extend earlier research by Herrera et al. (2019) and Shan et al. (2023), indicating that AI applications have evolved from short-term demand forecasting toward comprehensive water consumption assessment at regional and national scales.

The results of empirical studies also highlight AI's growing contribution to addressing water scarcity and climate resilience. Studies on water harvesting and scarcity mitigation indicate that AI can optimise water storage systems, improve resource allocation, and strengthen urban resilience to drought (Benitez et al., 2025), a finding that is particularly significant because many previous studies focused primarily on operational efficiency rather than broader sustainability outcomes. The evidence suggests that AI is not only a technological innovation but also a strategic instrument for achieving Sustainable Development Goal 6 and supporting climate adaptation efforts.

Despite these benefits, several challenges remain. One of the most frequently cited concerns is the dependence of AI systems on large volumes of high-quality data. Water management datasets often suffer from incompleteness, inconsistency, sensor failures, and geographic biases, particularly in developing countries. As a result, models trained on data-rich environments cannot perform effectively when applied to regions with limited monitoring infrastructure, raising concerns about the transferability and scalability of AI-based solutions across diverse hydrological and socio-economic contexts.

Another important challenge involves the transparency and explainability of AI models. While deep learning and neural-network architectures often achieve superior predictive performance, their "black-box" nature limits interpretability and reduces stakeholder confidence in decision-making processes. Recent studies on Explainable Artificial Intelligence (XAI) argue that improving model transparency is essential for increasing trust among policymakers, water managers, and the public. Without clear explanations of how predictions are generated, the adoption of AI-supported recommendations may remain limited despite their technical accuracy (El-dakhakhni et al., 2025).

The additional literature also reveals emerging governance and regulatory concerns. Wang et al. (2025) argue that AI has substantial potential to support regulatory compliance, policy monitoring, and evidence-based water governance. However, the integration of AI into institutional decision-making remains limited. Current water governance frameworks were largely designed before the emergence of advanced AI technologies and often lack clear guidelines regarding accountability, transparency, and algorithmic decision-making. Consequently, there is a growing need for regulatory frameworks that ensure responsible AI deployment while protecting public interests.

Ethical considerations further complicate the implementation of AI in water management. Richards et al. (2023) emphasise that although AI can improve service delivery and operational efficiency, it may also introduce risks related to cyber-security, algorithmic bias, digital inequality, and social exclusion. Communities with limited digital infrastructure may benefit less from AI innovations, potentially widening existing inequalities in access to water resources. Therefore, technological advancement must be accompanied by inclusive governance mechanisms that ensure equitable distribution of benefits.

Another critical issue concerns the balance between automation and human expertise. Fraternali et al. (2012) argue that effective water resource management requires human participation alongside intelligent systems. While AI can process large datasets and generate predictions rapidly, final decisions often involve social, political, environmental, and ethical considerations that extend beyond algorithmic analysis. Consequently, AI should be viewed as a decision-support tool rather than a replacement for professional judgment and stakeholder engagement.

The review also indicates a notable shift in research priorities. Earlier studies primarily focused on Artificial Neural Networks and forecasting accuracy (Ahmed et al. 2024), whereas contemporary research increasingly emphasises AIoT systems, digital twins, explainable AI, climate resilience, and governance integration. This evolution reflects the growing maturity of AI technologies and the recognition that sustainable water management requires interdisciplinary approaches combining technological innovation, environmental science, policy development, and stakeholder collaboration.

Finally, the evidence suggests that AI possesses substantial potential to transform water resource management. However, achieving this potential requires addressing challenges related to data quality, explainability, governance, ethics, and institutional adoption. Future research should therefore move beyond technical performance metrics and focus on developing trustworthy, transparent, and socially responsible AI systems that support sustainable and climate-resilient water governance across diverse global contexts.

6. Conclusion

AI is emerging as a transformative technology for sustainable water resource management, offering innovative solutions to increasingly complex water challenges driven by population growth, urbanization, climate change, and rising water demand. The findings of this study demonstrate that AI technologies, including machine learning, deep learning, artificial neural networks, explainable AI, and AI-enabled Internet of Things (AIoT) systems, significantly enhance water demand forecasting, water quality monitoring, drought prediction, infrastructure management, and decision-support processes.

The reviewed literature indicates that AI-based models consistently outperform conventional analytical approaches in predicting water consumption, assessing environmental conditions, and optimising resource allocation. Recent studies further demonstrate that AI can support large-scale water withdrawal estimation, domestic water-use assessment, and long-term forecasting of future water demand by integrating climatic, demographic, socio-economic, and land-use variables. These capabilities are increasingly important for supporting evidence-based planning and ensuring water security amid growing uncertainty.

The study also highlights the expanding role of AI in addressing water scarcity and climate resilience. AI-driven systems can optimise water harvesting, improve operational efficiency, reduce water losses, and strengthen adaptive capacity in regions facing increasing drought risk and resource constraints. Consequently, AI has significant potential to advance Sustainable Development Goal *six* and broader sustainability objectives by promoting more efficient, equitable, and resilient water management practices.

Despite earlier mentioned opportunities, several challenges continue to constrain the effective implementation of AI in water resource management. Data quality limitations, insufficient monitoring infrastructure, model opacity, cybersecurity risks, implementation costs, and concerns regarding transparency and accountability remain significant barriers, particularly in developing countries. Furthermore, the growing integration of AI into water governance raises important ethical and regulatory questions concerning algorithmic fairness, trustworthiness, and institutional responsibility.

The review suggests that the future success of AI in water management will depend not only on technological advancement but also on the development of robust governance frameworks, interdisciplinary collaboration, stakeholder participation, and responsible AI practices. Human expertise, local knowledge, and policy considerations must remain integral components of decision-making processes to ensure that AI systems support rather than replace informed professional judgment. Future research should focus on explainable and trustworthy AI models, climate-resilient water management systems, digital twins, AI-supported governance frameworks, and applications in data-scarce regions. Greater attention should also be given to evaluating the long-term environmental, economic, and social impacts of AI adoption in water systems. By addressing the above-mentioned challenges and opportunities, AI can play a pivotal role in building sustainable, adaptive, and resilient water resource management systems that meet the demands of future generations.

Transparency statement

The author confirms that this study has been conducted with honesty and in full adherence to ethical guidelines.

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Conflict of interest

The authors declare there are no conflicts of interest.

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