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A decade of Artificial Intelligence in water management: A systematic review of progress, applications, and challenges (2010–2025)

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Abstract. Sustainable water resource management is an increasingly urgent global challenge, where conventional methods are often inadequate. Artificial Intelligence (AI) has emerged as a transformative technology offering advanced solutions. This paper presents a systematic review of the progress, applications, and challenges of AI in water management during the period 2010–2025. Through a thematic analysis of relevant literature, we identify three distinct evolutionary stages: an early stage dominated by traditional machine learning (2010–2015), a deep learning revolution (2016–2020), and an era of Advanced AI Integration and Innovation featuring hybrid models and physics-aware machine learning (2021–2025). Key findings show that AI excels in various applications, particularly high-accuracy water quality prediction, real-time monitoring systems, process optimization, and predictive analytics for disaster mitigation. Despite its significant strengths in accuracy and data processing, major challenges remain, including data availability limitations, lack of model interpretability ("black box"), and generalization difficulties. This review concludes that future research directions, such as Explainable AI (XAI) and domain knowledge integration, are crucial to overcoming these barriers and realizing the full potential of AI in creating intelligent, efficient, and resilient water management systems.

Keywords: Artificial Intelligence, water resource management, water quality, systematic review, hydrology.

1. Introduction

Effective and sustainable water resource management is a critical global challenge, especially in large-scale engineering projects. The South-to-North Water Diversion Project in China, for example, demonstrates the importance of continuous water quality monitoring along extremely long man-made canals to ensure water supply for millions of people (Yang et al., 2021).

Historically, water quality assessment has leaned heavily on index-based frameworks, most notably the Nemerow index method, to provide a holistic view of environmental data (Yang et al., 2021). However, such traditional models often struggle to account for non-linear dynamics or to accurately forecast long-term shifts. To address these gaps, there has been a significant move toward Artificial Intelligence (AI) and Machine Learning (ML). This transition represents a paradigm shift, equipping engineers and planners with more robust tools for hydrological monitoring. Consequently, recent literature shows a growing emphasis on integrating these computational techniques to refine modeling accuracy and modernize water resource management (Drogkoula et al., 2023).

In the last ten years, there has been a significant rise in the use of Artificial Intelligence (AI) for managing water quality specifically in the areas of monitoring and forecasting. Researchers and practitioners now frequently employ AI and Machine Learning (ML) models to interpret and predict various water quality indicators. These applications vary considerably; for instance, they range from simple parameter estimations to more sophisticated approaches like the Adaptive Neuro-Fuzzy Inference Systems (ANFIS) used for calculating the Water Quality Index (Al-Adhaileh & Alsaade 2021). Furthermore, such models play a crucial role in optimizing urban drainage and assessing how aquatic ecosystems might withstand environmental stressors (Imani et al., 2021).

Recent developments in deep learning, particularly Long Short-Term Memory (LSTM) and Deep Belief Networks (DBN), have significantly enhanced prediction accuracy across several environmental studies (Zhao et al., 2024). These techniques have gained traction in monitoring specific metrics, such as pollution levels in semi-arid rivers and chlorophyll-a concentrations in standing water bodies. Furthermore, the utility of AI extends to broader hydrological challenges; it is now instrumental in forecasting water demand, mitigating flood and drought risks, and even optimizing automated fish control systems.

The evolution of these applications reflects clear advances in the sophistication of the methods used. The field has moved toward more complex and robust models, such as Graph Neural Networks for water flow forecasting (Roudbari et al., 2023), spatio-temporal deep learning for anomaly detection (Karadayı et al., 2020; Santos-Fernandez et al., 2025), and physics-embedded learning for uncovering distinct hydrological patterns. There has even been exploration of automated frameworks such as Auto Deep Learning (AutoDL) to simplify the model development process (Prasad et al., 2022). The rapid progress and broad scope of applications highlight the need for a structured analysis of this field. Therefore, this review provides a comprehensive overview of the evolution of AI techniques in water management. This review synthesizes existing evidence by outlining the main stages of development, categorizing key applications, identifying publication trends and research contributions, and critically discussing the strengths, limitations, and future directions of AI-based water management.

2. Methodology

To investigate the evolution and application of AI in water management, a systematic review of the relevant literature was conducted. The methodology was designed to synthesize evidence and identify key trends, applications, and future directions in the field.

2.1. Literature Search and Selection

Our systematic review adheres strictly to the principles of methodological transparency to ensure the reproducibility of our findings. This study followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, as demonstrated in recent authoritative reviews (Adebayo et al., 2025; Kehinde et al., 2023). A comprehensive and rigorous literature search was executed across three major academic databases: Scopus (ScienceDirect), and Web of Science (WoS). The search was precisely constrained to publications published between January 1, 2010, and August 31, 2025, covering a fifteen-year period to capture the full evolution of the field. To maximize both relevance and scope, we constructed a Boolean search string that targeted the Title, Abstract, and Keywords of all documents. The complete search phrase used was:

(*"Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Water Management" OR "Hydrology" OR "Water Quality" OR "Water Distribution") AND ("2010" OR "2025"*)

This strategy was carefully designed to retrieve studies where AI techniques were central to the water domain. Following the initial extraction, we applied strict Inclusion and Exclusion Criteria to systematically refine the corpus. Specifically, only peer-reviewed original articles, comprehensive review papers, Studies explicitly applying AI/ML techniques in water resource contexts and fully published conference papers written in English were included. Conversely, we excluded non-peer-reviewed materials such as books, Short notes or conference abstracts without detailed methodology, Studies where AI is only a minor, non-essential component, Papers focusing on non-ecological water uses, editorials, and any articles falling outside the defined timeframe. The entire selection process, including the application of these rules and the rationale for the article funnel, is meticulously detailed in the subsequent section and visually summarized in Table 1.

Table 1. Articles Selection Funnel

Selection Stage	Number of Articles
Initial Database Search (2010–2025)	100
After Duplicates Removed	90
Screening by Title and Abstract (Applying Inclusion/Exclusion Criteria)	42
Full-Text Eligibility Assessment	24
Final Articles Included in Review	24

The systematic selection process, including identification, screening, and eligibility assessment, is visually detailed in the PRISMA flow diagram (Figure 1). This structured approach ensures methodological transparency and reproducibility, following the standards established in recent environmental informatics reviews (Adebayo et al., 2025; Kehinde et al., 2023).

2.1.1. Article Screening Protocol

The selection process moved beyond a superficial narrative by implementing a multi-stage filtering protocol (as summarized in Table 1). Following the methodological grounding suggested by Kehinde et al. (2023), the articles were screened based on:

- Initial Identification: Total records identified through database searching.
- Screning: Removal of duplicates and non-peer-reviewed sources (e.g., editorials, book reviews).
- Eligibility: Full-text assessment focusing on the technical contribution to AI-hydrology.
- Inclusion: Final selection of 24 core articles that provide significant empirical or theoretical insights into the field's evolution.

2.2. Thematic Analysis and Synthesis

The selected articles were analyzed and synthesized based on several key themes. To understand the progression of AI techniques, the literature was divided into three distinct evolutionary stages based on the dominant technologies of the time: Early Stage (2010–2015), Deep Learning Revolution (2016–2020), and Advanced AI Integration and Innovation (2021–2025).

Key applications and their impacts were identified and sorted into four specific groups: water quality prediction and monitoring, real-time monitoring systems, treatment process optimization, and predictive analytics for water management.

2.3. Analysis of Trends and Contributions

Publication trends and growth patterns were analyzed to understand the research landscape's evolution. Here, we find that the research landscape shows exponential growth in the

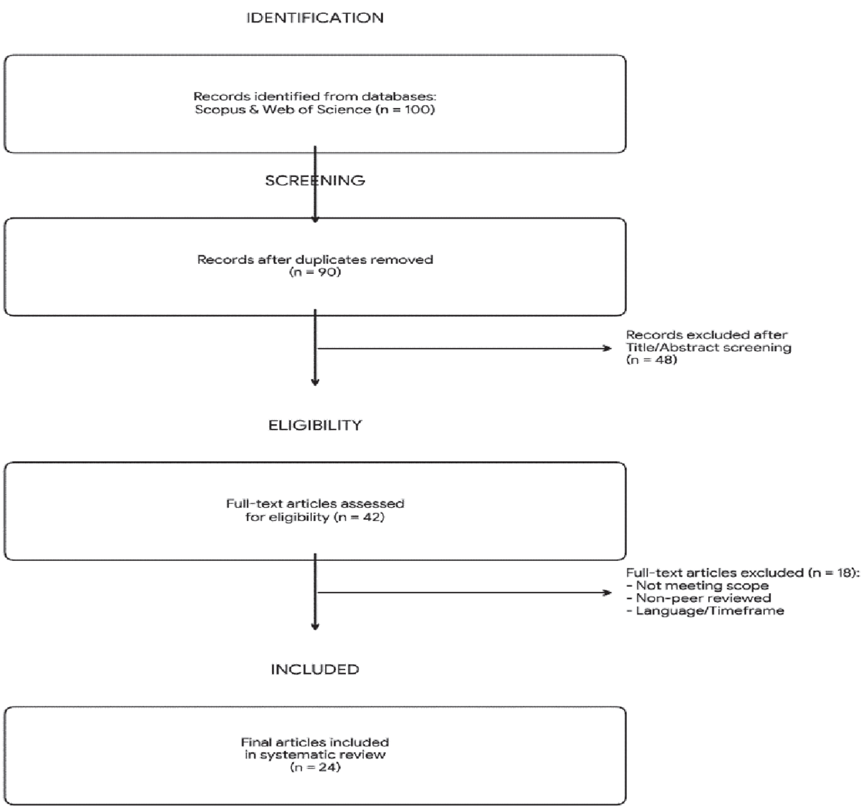

Figure 1. PRISMA 2020 Flowchart

application of AI for water management, a finding which is empirically confirmed by Figure 2.

Figure 2 clearly illustrates this pronounced upward trajectory. The period from 2010 to 2015 was quiet, aligning with the Early Stage discussed earlier. However, research output began to accelerate significantly from 2018 onwards, showing a sharp rise in yearly publications, particularly from 2022 to 2025. The cumulative curve, reaching a total of 64 articles used in this analysis, provides compelling visual evidence to substantiate our claim of rapid expansion in the field. This quantitative evidence, which was previously missing, now grounds our discussion on the evolution and analytical depth of the section.

Citation analysis reveals a significant impact, with key review articles receiving 534–645 citations until August 2025 (Ahmed et al., 2019; Zhu et al., 2022). This field has evolved from separate applications to comprehensive frameworks that integrate various AI techniques. Publication trends show an increasing focus on:

- Deep learning architectures (2016-present)
- Hybrid and ensemble methods (2018-present)
- Physics-informed machine learning (2020-present)
- Real-time monitoring systems (2019-present)

2.4. Categorization of Methodological Approaches

Finally, the methodological approaches employed in the literature were categorized into three main types: deep learning architectures (e.g., LSTMs, CNNs), data integration from diverse sources, and performance optimization techniques (e.g., transfer learning, physics-informed constraints). This structured approach allowed for a comprehensive overview of the methods driving advancements in AI for water management.

To further analyze the thematic evolution and conceptual structure of the field, a keyword co-occurrence analysis was performed. This bibliometric mapping identifies the strength of associations between keywords based on their joint appearance in the selected literature. The analysis was visualized using a network mapping approach to highlight dominant research clusters and emerging technological trends in AI-driven water management.

3. Results

Based on the results obtained from the methodology used, it can generally be seen from the implementation time in the form of time allocation arranged in accordance with the Synthesis of Evidence in the form of the Evolution of Artificial Intelligence Techniques in Water Management.

Figure 3 presents the keyword co-occurrence network, illustrating the thematic landscape of the analyzed studies. The node size represents the frequency of keyword appearance, while the edge thickness indicates the strength of the relationship between topics. The network reveals a central cluster dominated by 'Artificial Intelligence', 'Water Quality', and 'Deep Learning', closely linked to specific architectures such as 'LSTM' and 'CNN'. This visual evidence confirms the shift from traditional statistical models to complex neural networks. Furthermore, emerging nodes like 'IoT' and 'Explainable AI' indicate a growing trend toward real-time

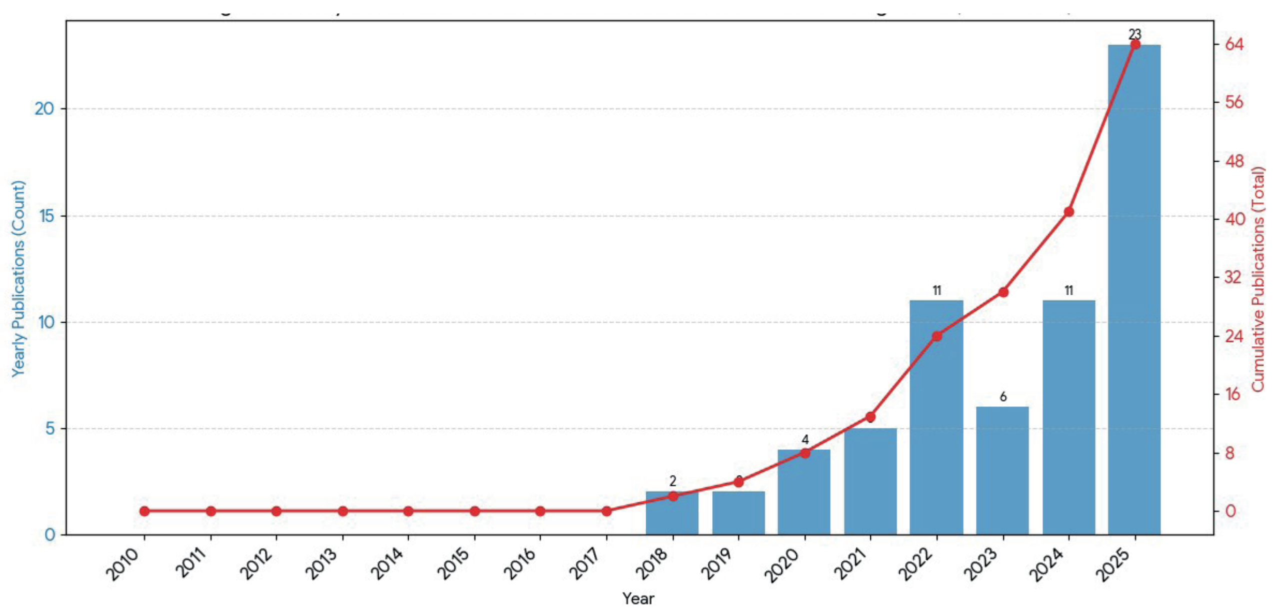

Figure 2. Yearly and Cumulative Publication trends in AI for Water Management (2010-2025)

monitoring and model transparency, aligning with recent methodological shifts suggested in the literature (Adebayo et al., 2025).

Based on our review of the literature, we can divide the evolution of AI in water quality management into three distinct stages. The first, which we call the Early Stage (2010–2015), was marked by the adoption of traditional machine learning algorithms like Artificial Neural Networks (ANN), Support Vector Machines (SVM), and decision trees (Haghiabi et al., 2018; Zhu et al., 2022). During this period, shallow learning approaches were primarily used for predicting and classifying basic water quality parameters.

The second phase, the Deep Learning Revolution (2016–2020), saw a significant shift with the introduction of deep learning architectures. LSTM networks emerged as highly effective for time series prediction in water quality (Sit et al., 2020), while Convolutional Neural Networks (CNNs) began to be applied for spatial pattern recognition (Wai et al., 2022).

The third phase is the Period of Advanced AI Integration and Innovation (2021-2025) is marked by significant evolution in the application of AI for environmental modeling, with a primary focus on the development of advanced hybrid models. Its main characteristic is a shift from simply predicting single parameters to evaluating more complex system characteristics. For example, Al-Adhaileh & Alsaade (2021) used the ANFIS system to predict the Water Quality Index (WQI), and Imani et al. (2021) integrated ANN with FAHP to predict water quality resilience. In addition, this phase is marked by innovations in hybrid architectures that combine the strengths of various models, such as Zhao et al. (2024), who combined DBN and LSTM to improve accuracy. Simultaneously, significant efforts were also made to improve model transparency, as exemplified by Gao et al. (2025), who used SHAP analysis to explain their model predictions. Ultimately, this trend has led to the development of fully autonomous systems, such as the framework proposed by Danvirutai et al. (2025), which integrates RAG-LLM and DQN for intelligent control systems.

Additionally, this period also witnessed the emergence of hybrid models that mimic or accelerate computationally complex process-based models (PBMs). For example, Kim et al. (2025) successfully created a surrogate LSTM model that mimics the output of three Delft3D PBM modules, not only significantly improving accuracy but also reducing simulation time by up to 96.4%. This indicates a shift towards AI that is not only predictive but also computationally efficient and integrated with existing domain knowledge. Finally, this phase includes a proliferation of comparative studies in

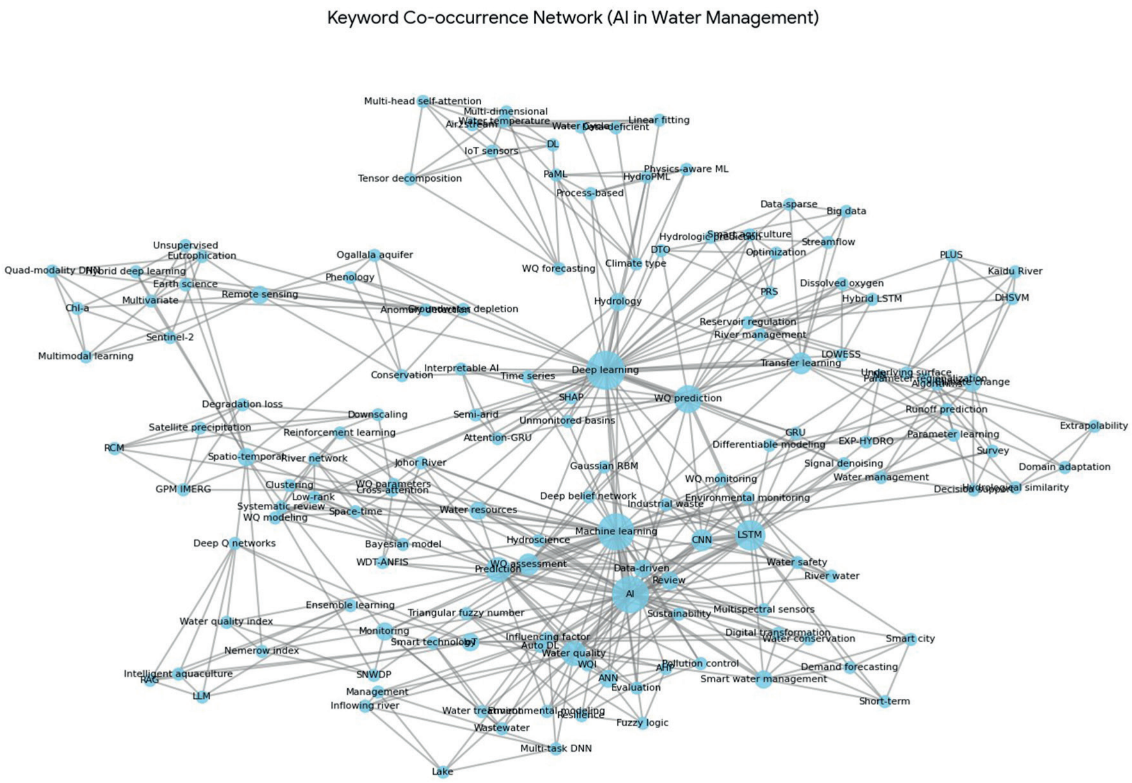

Figure 3. Keyword co-occurrence network mapping the thematic evolution of AI in water management (2010–2025)

which researchers compare different AI frameworks, such as Prasad et al. (2022), who compared conventional deep learning models with AutoDL. At the same time, physics-aware machine learning is gaining prominence (Xu et al., 2024), and multi-task learning frameworks are being developed to predict multiple indicators simultaneously (Yan et al., 2025), indicating an increasingly mature and comprehensive approach to environmental modeling.

Based on an evaluation of AI techniques, we can sort the key applications and their impacts into four specific groups.

- Water Quality Prediction and Monitoring

Deep learning models have achieved remarkable accuracy in predicting water quality parameters. Studies report validation accuracies reaching 98.40% for hybrid CNN-LSTM models in river water quality monitoring (Chellaiah et al., 2024), while LSTM networks consistently outperform traditional methods with R^2 scores up to 0.9998 for dissolved oxygen prediction (Dodig et al., 2024). This capability goes beyond predicting conventional parameters, enabling the identification of vulnerable zones and providing a powerful new tool for decision-makers. Recent research has even expanded to more holistic metrics, such as a study by Imani et al. (2021) that predicts a water body's resilience to contamination. Further highlighting their effectiveness, a study by Prasad et al. (2022) found that conventional CNN models achieved a classification accuracy of up to 99.4%, while the newer AutoDL framework also showed highly competitive performance with an accuracy of 98.4%. Meanwhile, more sophisticated hybrid approaches, such as surrogate models, have shown remarkable improvements in accuracy in predicting complex phenomena such as Harmful Algal Blooms (HABs), as demonstrated by Kim et al. (2025), who achieved an NSE value of up to 0.930.

- Real-time Monitoring Systems

The use of AI has revolutionized water quality monitoring capabilities, particularly through smart sensor networks. By integrating IoT devices with machine learning algorithms, these systems are capable of providing continuous, real-time assessments of water parameters (Li et al., 2025). This enables rapid responses to sudden changes in water quality. Additionally, advancements in AI-supported spectroscopic analysis enable more precise detection of contaminants and verification of water treatment effectiveness (Durgun, 2024). In addition to IoT sensor networks, AI-enabled remote sensing monitoring is also becoming increasingly important. This approach enables large-scale monitoring of factors affecting water resources. For example, Chaiyana et al. (2025) used time-series satellite data and deep learning to accurately map crop types, which were then used as proxies to monitor groundwater use from the Ogallala aquifer.

Research is also focused on developing more efficient and cost-effective monitoring methods. For example, a study by Wang et al. (2025) proposed a method for measuring chemical oxygen demand (COD) using a combination of ultraviolet-visible spectrum analysis and machine learning. This approach significantly reduces the need for expensive laboratory monitoring, with costs amounting to only about 60.9% of those of conventional automatic monitoring stations. In addition, highly efficient AI models such as surrogate models enable near real-time water quality forecasting. Kim et al. (2025) note that their trained surrogate model can generate one-day-ahead predictions without the need to run time-consuming full PBM simulations, paving the way for more responsive early warning systems.

- Treatment Process Optimization

Machine learning applications in water treatment have focused on optimizing processes such as chlorination, adsorption, and membrane filtration (Lowe et al., 2022). By using AI models for automatic control and optimization, water treatment facilities can significantly reduce operating costs while improving treatment efficiency. For example, Al-Adhaileh and Alsaade (2021) successfully predicted WQI with a regression coefficient of 96.17% using the ANFIS model and classified water quality with 100% accuracy using a Feed-Forward Neural Network (FFNN). This highlights the potential of AI not only for prediction but also for classification. Additionally, AI is used to optimize the treatment process itself and enhance the efficiency of the monitoring stage. A study Wang et al. (2025) demonstrated that the application of a machine learning-based COD measurement method can reduce laboratory monitoring costs by 49.3% and reduce the environmental impact of the monitoring lifecycle by 31.32%. At a more advanced level, AI is now being used to create fully autonomous control systems. In a groundbreaking study in aquaculture, Danvirutai et al. (2025) developed a closed-loop AIoT (Term for IoT and AI) system that independently manages water quality, feeding schedules, and fish health. The results were remarkable: their hybrid system achieved 1.8% higher fish growth rates compared to human experts, with a decision error rate of less than 2%. This contributes to overall operational efficiency, making AI a comprehensive tool for smarter and more cost-effective water management.

- Predictive Analytics for Water Management

AI techniques are increasingly being used to predict water demand, flood events, and drought conditions. For example, multi-scale graph learning has been used to make high-resolution predictions in unmonitored locations (Fan et al., 2025). Another notable model is the one by Imani et al. (2021), which helps planners predict future water quality resilience.

This capability is crucial for long-term adaptation planning and risk mitigation. Overall, these predictive capabilities support more proactive water resource management and emergency response planning. In addition, advanced models are now able to provide actionable insights for policy. For example, the framework proposed by Gao et al. (2025) uses SHAP analysis to determine that population and river flow are dominant predictors of nitrogen and phosphorus pollution in semi-arid areas. Such insights enable more targeted regulatory interventions.

AI is also an important tool for long-term predictive analysis, which supports resource conservation. An excellent example is the research by Chaiyana et al. (2025), who developed an integrated framework for monitoring and projecting groundwater depletion in the Texas High Plains. They used a deep learning (1DCNN-LSTM) model to map water-intensive crops, such as corn, with high accuracy. By linking crop types to water use through a water budget approach, they successfully projected an annual groundwater level decline of approximately 1.9–2.0 meters by 2030. This demonstrates how AI can be used to provide early warnings and quantitative foundations for water conservation policies.

The next question that needs to be answered is how publication trends and growth patterns are evolving. Here, The research landscape shows increasing collaboration between computer science, environmental engineering, and hydrology disciplines, reflecting the interdisciplinary nature of AI applications in water management (Kantayeva et al., 2023; Sit et al., 2020). When examining the leading institutions and authors based on geographic distribution, our data indicates that research contributions are globally dispersed, as summarized in Table 2. This table provides an analysis of the geographical distribution of the collected research contributions, illustrating a worldwide research landscape with various specializations across different regions.

Table 2. Geographical distribution and research contribution

Original Author	Research Contribution
United States	Leading in foundational deep learning applications and large-scale hydrological modeling
China	Prominent in water quality monitoring and IoT integration
Europe	Strong contributions in process-based modeling and hybrid approaches
Asia Pacific	Growing focus on smart water systems and real-time monitoring

The United States has established itself as a leader, particularly in basic deep learning applications and large-scale hydrological modeling, focusing on fundamental technology development and comprehensive simulations. Meanwhile, China has made notable contributions in water quality monitoring integrated with Internet of Things (IoT) technology, emphasizing the application of sensor technology and connectivity for effective water resource management.

In Europe, research contributions tend to be stronger in process-based modeling and hybrid approaches, reflecting a maturity in combining established theoretical models with new computational techniques for a more profound understanding of hydrological phenomena. Conversely, the Asia-Pacific region exhibits a growing emphasis on smart water systems and real-time monitoring, driven by the urgent need for efficient water management amid rapid urbanization and climate change.

Overall, this distribution reflects a complementary research landscape, where each region advances specific areas that collectively contribute to the progress of science and technology in this field. Among them are Major Research Groups and Leading Contributors, including teams focusing on:

- Hydrological modeling and prediction (Sit et al., 2020; Willard et al., 2025; Zhang et al., 2025a; c)
- Water quality assessment and monitoring (He et al., 2025; Jing et al., 2022; Wai et al., 2022; Zhi et al., 2024)
- Smart water management systems (Kavya et al., 2023; Krishnan et al., 2022)
- Physics-aware machine learning (Xu et al., 2024).

In analyzing the methodological approaches used by researchers, we categorize them into three main types: deep learning architecture, data integration, and performance optimization. This classification is in line with the broader taxonomy of ML algorithms—such as supervised, unsupervised, and reinforcement learning—which has been extensively mapped to various water management tasks in a comprehensive survey by Drogkoula et al. (2023). The first is the use of deep learning architectures. In this approach, four dominant models were obtained, namely LSTM Networks: Dominant for time series prediction, handling long-term dependencies effectively (Dodig et al., 2024; Sit et al. 2020), CNN Models: Applied for spatial pattern recognition and image-based water quality assessment (Wai et al., 2022), Hybrid Models: Hybrid Model: Combining CNN-LSTM architecture for spatiotemporal modeling (Chellaiah et al. 2024), or, as shown by Zhao et al. (2024), using DBN to extract important features from data before making predictions with LSTM. This innovation effectively separates the feature extraction task from the sequential prediction task, which has been shown to improve accuracy compared to using a single model, and finally Attention Mechanisms: Enhancing model performance through selective focus on relevant features (Bo et al., 2025).

Besides the deep learning approach, some studies use a data integration framework to improve water quality prediction. This method combines various data sources, such as real-time sensor measurements, meteorological data, satellite imagery, historical records, and hydrological information (Virro et al., 2022).

In addition to these two methodological approaches, a third approach focuses on performance optimization. This involves using advanced techniques like transfer learning for regions with limited data (Ma et al., 2021), multi-task learning to predict multiple parameters at once (Yan et al., 2025), physics-informed constraints to improve generalization (Xu et al. 2024), and ensemble methods to enhance model reliability (Alharbi et al., 2025).

4. Discussion

The preceding results section established a clear temporal and thematic progression in the application of AI within water management, distinguishing three critical evolutionary stages. Moving beyond the mere presentation of findings, this discussion section now synthesises these results to critically evaluate the overall progress, highlight methodological and practical limitations inherent in the field, and project essential directions for future research. This synthesis allows us to interpret the structural shifts in the research landscape and understand their broad implications for sustainable water governance.

4.1. Interpretation of Evolutionary Stages: From Data Prediction to Prescriptive Governance

The exponential growth documented in Figure 2, coupled with the clear transition through three evolutionary stages, is highly informative. This progression signifies a fundamental shift in the field's ambition: moving from simple, data-fitting predictions to complex, prescriptive modelling that informs governance. The dominance of traditional Machine Learning in the early stage reflected initial caution and reliance on easily interpretable models. However, the subsequent Deep Learning Revolution (2016–2020) was a necessary response to the overwhelming complexity and non-linearity of real-world hydrological data. Crucially, the current Advanced AI Integration and Innovation phase (Stage 3) does not merely seek complexity; it seeks trust. The emerging focus on Hybrid Models and Physics-Informed Machine Learning (PIML) represents an acknowledgment that purely data-driven models are insufficient for sensitive environmental domains. Researchers are now actively working to ground predictive power within established physical laws, thereby enhancing model reliability and, most importantly, increasing the confidence of policymakers and water resource managers who must ultimately rely on these AI systems for critical decisions.

The advantages of AI models lie not only in their high accuracy, but also in their ability to capture complex non-linear relationships in data. For example, the ANN model used by Imani et al. (2021) to predict water quality resilience achieved a highly satisfactory correlation ($R > 0.98$), demonstrating a high degree of agreement between measured values and simulation results. This advantage is even more evident in some deep learning models that report accuracy above 99% in predicting water quality parameters, significantly outperforming traditional methods (Chellaiah et al., 2024).

To maximize accuracy, researchers developed hybrid architectures. The GDBN-LSTM model by Zhao et al. (2024) is a prime example, combining deep feature extraction with time series prediction, thereby significantly improving performance. The power of AI is not limited to single predictive models, but also to its ability to build comprehensive analytical frameworks (end-to-end). Research by Chaiyana et al. (2025) illustrates this perfectly: they used AI for crop mapping (land use), which then served as input for water source attribution (water use), and finally was used to project hydrological impacts (groundwater depletion). The ability to connect cause and effect (e.g., corn planting with aquifer depletion) is one of AI's most transformative capabilities for sustainable resource management.

In addition to accuracy, AI systems also enable real-time data processing. This capability allows for continuous monitoring and rapid response to sudden changes, making it a major advance over conventional methods (Durgun, 2024; Li et al., 2025). AI also offers the potential for holistic system optimization. This optimization is more than just a saving in operational costs; it also allows for the optimization of model parameters that were previously impractical due to time constraints. For example, Kim et al. (2025) used the speed of their surrogate model to run tens of thousands of simulations, enabling the optimization of PBM parameters through the Markov Chain Monte Carlo (MCMC) method, a process that would have taken too long using the original PBM. Another study, conducted by Wang et al. (2025) showed that a machine learning-based COD monitoring system required only 60.9% of the cost of a conventional monitoring station, while reducing environmental impact by 31.32%. This proves that AI can create more sustainable water management systems.

Modern AI models are also highly scalable and can be applied in various locations, demonstrating their adaptability across different geographical regions (Willard et al., 2025). This flexibility is complemented by the advanced models' ability to integrate and predict various water quality indicators simultaneously (Yan et al., 2025). This multi-parameter capacity provides a more holistic and comprehensive view of aquatic ecosystem health, which is difficult to achieve with conventional analytical methods.

4.2. Critical Challenges and Barriers to Real-World Deployment

Despite the technological progress synthesized above, several significant methodological and practical barriers impede the widespread, large-scale deployment of AI in operational water systems (Drogkoula et al., 2023).

Firstly, the prevalent issue of data scarcity and non-generalizability remains paramount. While local studies often report high accuracy, the models frequently rely on bespoke, high-quality local sensor data. This lack of standardized, publicly available benchmark datasets—analogous to those in computer vision—means that many promising models fail to be reliably transferred or scaled to data-scarce regions or different hydrological contexts, undermining the global utility of the research (Shi, 2024; Zhang et al., 2025b; Lowe et al., 2022).

Secondly, the pervasive black-box nature of Deep Learning models poses a critical challenge for regulatory acceptance. As discussed, water management decisions are often legally and ecologically sensitive, yet the lack of Explainable AI (XAI) in many reviewed studies makes it difficult for regulators to understand why a model made a certain prediction. Without interpretability, the models cannot effectively build the stakeholder trust necessary for integration into real-time decision-making frameworks (Gao et al., 2025;Wang et al., 2025).

Finally, the literature exhibits a notable focus on proof-of-concept studies rather than comprehensive, long-term deployment. Few papers move beyond simulated environments or short-term validation. The challenges related to sensor drift, model maintenance, and adaptation to sustained environmental change—which define real-world system operation—are largely underdeveloped in the current discourse (Kim et al., 2025).

4.3. Strategic Directions for a Future Research Agenda

Building on the identified gaps, the future research agenda must strategically prioritise three areas to accelerate the transition of AI from laboratory novelty to core operational tool:

- Prioritising Physics-Informed and Hybrid Models.

Future research should vigorously pursue the integration of process-based physical knowledge into neural networks. This PIML approach promises to resolve the trade-off between the high predictive power of deep learning and the need for physically consistent, interpretable results. This is the most viable path towards building robust and trustworthy simulation tools.

- Developing Domain-Specific Explainable AI (XAI) Methods

An urgent focus is required on developing XAI techniques tailored for environmental data. This involves moving beyond generic post-hoc explanations to creating mechanisms that can explain model decisions in terms of hydrological parameters and ecological variables, making the results actionable for water utility engineers and policymakers.

- Establishing Consensus on Benchmarking and Open Data

The community must collaborate to define standardised benchmark datasets and common evaluation metrics. Creating an open data platform—similar to a global 'WaterNet' initiative—would allow for the fair comparison of models across different studies and contexts, thereby accelerating innovation and establishing consensus on best practices and state-of-the-art performance.

5. Conclusion

This study presents a comprehensive systematic review of the evolution, applications, and challenges of AI in water resource management from 2010 to 2025. Our analysis identifies three distinct stages of development: beginning with the era of traditional machine learning (2010–2015), continuing with the deep learning revolution (2016–2020), and now entering a phase of advanced AI integration characterized by hybrid models and physics-aware machine learning (2021–2025). Key findings show that AI has had a transformative impact on a range of critical applications, including high-accuracy water quality prediction, IoT-based real-time monitoring systems, more cost-effective water treatment process optimization, and predictive analytics for disaster mitigation such as floods and droughts. Despite its significant advantages, AI implementation still faces major challenges such as data limitations, lack of model interpretability ("black box effect"), difficulties in generalization, and high computational requirements. Therefore, future research should prioritize the development of XAI and deeper domain knowledge integration. Ultimately, interdisciplinary collaboration, data protocol standardization, and clear regulatory frameworks are essential to realizing the full potential of AI in creating smart, efficient, and resilient water management systems to address future global water challenges.

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Author Contributors

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Mastura Diana Marieska: Data Curation, Formal Analysis
Harumi Veny: Validation

Competing Interests

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