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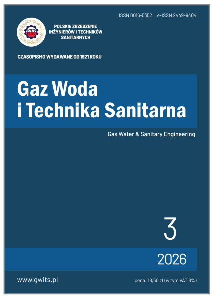


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# Artificial intelligence for hydraulic and water resources engineering: Challenges, opportunities and a research agenda

## Sztuczna inteligencja w inżynierii wodnej i hydraulice: wyzwania, możliwości i program badawczy

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**Abstract:**
Artificial intelligence (AI) and machine learning (ML) are essential in addressing water scarcity and ensuring access to clean water. These technologies have become integral to hydraulic engineering and water resource management, enhancing the management and optimization of water systems. They are employed in various applications, including optimizing and designing water treatment processes, monitoring water quality, tracking water consumption, managing groundwater resources, and supporting river engineering and flood management. Furthermore, they are instrumental in tackling hydrological challenges, such as those posed by climate change, thereby improving efficiency and effectiveness in water resource management.
**Keywords:** artificial intelligence, water resource management, machine learning, water domain

**Streszczenie:**
Sztuczna inteligencja (AI – artificial intelligence) i uczenie maszynowe (ML – machine learning) odgrywają kluczową rolę w rozwiązywaniu problemu niedoboru wody i zapewnianiu dostępu do czystej wody. Technologie te stały się integralną częścią inżynierii wodnej i zarządzania zasobami wodnymi, usprawniając zarządzanie i optymalizację systemów wodnych. Są one wykorzystywane w różnych zastosowaniach, w tym w optymalizacji i projektowaniu procesów uzdatniania wody, monitorowaniu jakości wody, śledzeniu zużycia wody, zarządzaniu zasobami wód podziemnych oraz wspieraniu inżynierii rzecznej i zarządzania powodziami. Ponadto odgrywają one kluczową rolę w rozwiązywaniu problemów hydrologicznych, takich jak te związane ze zmianami klimatu, poprawiając tym samym efektywność i skuteczność zarządzania zasobami wodnymi.
**Słowa kluczowe:** sztuczna inteligencja, zarządzanie zasobami wodnymi, uczenie maszynowe, dziedzina wody

## 1. Introduction

The growing scarcity of freshwater resources, exacerbated by climate change, population growth, and urbanization, presents a pressing global challenge. Water resources management (WRM) must prioritize efficiency, effectiveness, and adaptability to address these challenges. Artificial intelligence (AI) and machine learning (ML) offer powerful tools to achieve these goals, with applications in irrigation optimization, water quality monitoring, flood prediction, and water demand forecasting. These AI applications significantly enhance agricultural practices and water distribution systems. Artificial intelligence (AI) simulates human intelligence in machines, allowing them to perform tasks that typically require human intellect, such as learning, reasoning, and problem-solving. Machine learning (ML) is a subset of artificial intelligence that focuses on building algorithms and statistical models, enabling computers to learn from data without explicit programming. By employing advanced algorithms, AI and ML can create predictive models that forecast water availability, demand, and potential risks, such as floods or droughts. These models can help stakeholders make informed decisions and implement proactive measures to manage water resources effec-

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tively. AI and ML can process vast amounts of data from diverse sources—such as remote sensing, ground sensors, and citizen science—providing a more comprehensive and timely picture of water systems. This capability allows for improved monitoring of water quality, quantity, and distribution [6]. The hierarchical representation of artificial intelligence, machine, and deep learning are shown in Fig 1.

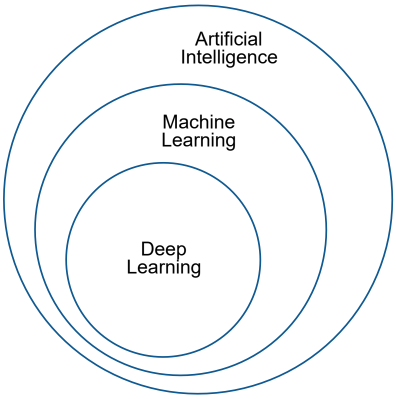


**Fig. 1**. The representation of artificial intelligence, machine and deep learning
**Rys. 1.** Struktura sztucznej inteligencji, uczenia maszynowego i głębokiego uczenia

In recent decades, the Artificial intelligence (AI) and machine learning approach has gained significant traction as a powerful alternative to traditional scientific discovery methods. This shift has opened up numerous opportunities and challenges across various fields, including hydraulic engineering, subsurface reservoirs, watershed engineering, and water resources management. Filo [11] highlights that artificial intelligence (AI) and machine learning (ML) have numerous applications in water resource management. Between 2013 and 2023, the number of publications in this area, as shown in Fig. 2, indicates that articles and conference papers account for over 90% of the documents reviewed. The publication landscape is diverse, with Engineering and Computer Science leading in numbers, followed by significant contributions from Environmental Science, Earth Science, and Energy. This diversity underscores the broad applicability of AI technologies and their potential for future development across various fields.

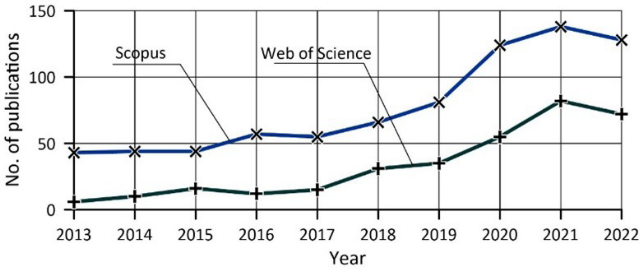


**Fig. 2**. The number of Scopus-and WoS-indexed publications on AI methods in hydraulic between 2013 and 2022 [11]
**Rys. 2.** Liczba publikacji indeksowanych w bazach Scopus i WoS na temat metod sztucznej inteligencji w hydraulice w latach 2013–2022 [11]

In the following, recent studies on artificial intelligence (AI) in hydraulic engineering and water resources management are discussed briefly. Various applications have been investigated, and this analysis is categorized into four main areas, along with the related challenges and opportunities.

## 1.1. Category 1: optimizing water treatment and water quality monitoring

Ensuring sustainable and clean water access is vital for water and wastewater treatment facilities, as well as for numerous natural and industrial systems that depend on this essential resource. One significant contribution of artificial intelligence (AI) and machine learning (ML) is in the realm of water quality monitoring. Artificial intelligence methods and machine learning models have proven effective in optimizing, modeling, and automating crucial operations in water treatment, monitoring of natural systems, and water-based agricultural practices, including hydroponics and aquaponics. These algorithms can analyze historical data to identify patterns and detect anomalies in key water quality indicators such as temperature, pH, dissolved oxygen, and nutrient levels. Furthermore, AI and ML can be utilized to forecast the occurrence of harmful algal blooms and other significant water quality issues.

Zhang et al. [47] evaluated a deep learning model that utilizes long short-term memory (LSTM) networks to detect time-delayed water quality indicators (WQIs) in wastewater treatment plant (WWTP) influent. The authors highlighted the importance of rapid and precise detection of WQIs for efficient plant operation, especially under varying sewage loads. They noted that traditional machine learning methods often fall short in accuracy, prompting the development of their LSTM approach. To enhance model interpretability, they applied global sensitivity analysis (GSA) using Shapley additive explanations (SHAP) to assess the impact of input indicators. Their case study demonstrated that the LSTM models effectively identified key pollutants, such as chemical oxygen demand, total nitrogen, and total phosphorus, outperforming several baseline models. This innovative combination of deep learning and GSA offers a promising solution for improving the sustainability and efficiency of WWTP operations. In [7] water quality index (WQI) models were optimized using machine learning. By combining machine learning and game theory, they developed combined weights to improve model accuracy, particularly in the Chaobai River Basin. The study introduced two new aggregation functions: SWM and LQM. Three WQI models were created, with WQIS recommended for poor water quality and WQIW for good quality. This research offered valuable insights for future water quality assessments and environmental protection. The investigations in [4, 20, 29] collectively underscored the significant role of machine learning and artificial intelligence (AI) in advancing water treatment and monitoring processes. Lowe et al. [29] provided a comprehensive review of how smart technologies integrate with AI to enhance water treatment efficacy and monitoring capabilities. Al Aani et al. [4] explored the potential of machine learning and AI to revolutionize process automation in water treatment and desalination, highlighting the transformative impact these technologies can have. Jawad et al. [20] focused on the application of artificial neural networks in modeling wastewater treatment and desalination through membrane processes, showcasing innovative approaches to improve efficiency. Taloba [43] further evaluated the use of artificial neural networks specifically for optimizing energy consumption in water treatment and desalination facilities, which are crucial for providing clean drinking water. Given that these facilities are energy-intensive and contribute to greenhouse gas emissions, Taloba [43] emphasized the importance of energy optimization for environmental sustainability and economic efficiency. Collectively, these studies illustrate how AI and machine learning can address the challenges of water treatment, improve operational efficiency, and promote sustainable practices in the water sector.

### 1.2. Category 2: water consumption monitoring, water allocation, and groundwater management

Artificial intelligence and machine learning applications in water management extend beyond water quality to include water consumption monitoring, demand forecasting, irrigation optimization, and allocation. These technologies can develop models that optimize irrigation planning and reduce water consumption. Additionally, real-time water consumption monitoring enables the identification of high-usage areas and facilitates the development of water conservation plans. A review of research in [5, 24, 25, 45] highlights AI's transformative potential in smart water resource management. These studies explored AI applications in optimizing water management practices, short-term water demand forecasting, and water quality management. They emphasized the importance of machine learning algorithms in analyzing historical data and making accurate predictions. These findings underscore AI's crucial role in fostering sustainable water management practices across agricultural and urban contexts, addressing the growing challenges of water scarcity and resource optimization.

Goralski and Tan [15] highlighted the transformative potential of artificial intelligence (AI) in advancing sustainable water resource management. They emphasized that AI can provide real-time data on water availability and usage, which is crucial for optimizing water allocation and reducing waste. For example, AI-enabled sensors in irrigation systems empower farmers to fine-tune their water consumption practices, leading to reduced water loss and enhanced crop yields. Additionally, AI's capability to monitor water quality in real time allows for the swift identification of contaminated sources, safeguarding public health by preventing the use of unsafe water for consumption. In urban settings, AI applications extend to monitoring overall water consumption, detecting leaks in distribution systems, and prioritizing maintenance tasks, thereby improving the efficiency and reliability of water supply infrastructure. Chang et al. [6], Zekrifa et al. [50], Ghobadi and Kang [12] and Sit et al. [39] highlighted AI's transformative potential in hydrology and water resources management. These studies addressed the critical challenges of urban water management, including rising population, increased demand, and deteriorating water quality. AI offers innovative solutions like water quality monitoring, leakage detection, demand forecasting, flood management, water purification, and smart irrigation. Zekrifa et al. [50] explored AI integration for improved hydrological modeling, while Ghobadi and Kang [12] provide a systematic literature review on AI applications in water resources management. Sit et al. [39] evaluated deep learning's transformative potential in hydrology. Doorn [8] explored the current applications of artificial intelligence (AI) in the water sector and suggested what „responsible AI" might entail in this context. She emphasizes that developing and applying responsible AI techniques should involve collaboration between water professionals and data scientists, as well as input from experts in the social sciences and humanities. Also, AI can enhance water conservation efforts by identifying areas of waste and recommending strategies to minimize consumption. For example, AI-enabled smart meters can track household water usage and detect instances of excessive consumption. This information can be used to provide consumers with feedback and suggestions for reducing their water use, thereby promoting more sustainable water practices. Collectively, these studies demonstrate AI's ability to enhance efficiency, sustainability, and responsiveness in water management systems, addressing modern water resource challenges.

### 1.3. Category 3: river engineering and flood management

Floods pose significant threats to infrastructure and human safety. Accurate flood forecasting and control are crucial for mitigation. Deep learning, with its ability to process vast amounts of data and provide precise predictions, offers a powerful tool for improving flood management. AI and ML can develop flood forecasting models that accurately predict timing and spatial extent. Additionally, these technologies can analyze river and watershed data to identify erosion-prone areas and inform effective erosion control programs. By focusing on vulnerable areas, AI enhances water resource management and promotes environmental sustainability.

Kabir et al. [21] developed a machine-learning framework for forecasting and visualizing flood inundation information. This innovative approach combines various machine learning algorithms to generate probabilistic flood inundation maps with a three-hour lead time. By employing rainfall-discharge models using a random forest technique alongside multi-layer perceptron classifiers, the framework effectively classifies wet and dry areas. Tested on data from a fluvial flood event in a flood-prone town in the UK, the model demonstrated high accuracy, with a mean arrival time difference of just 1 hour and 53 minutes compared to a traditional hydrodynamic model. Notably, this framework is user-friendly, efficiently identifies flooded areas, and significantly reduces computational time, making it a valuable tool for real-time flood management. Ekwueme [10] examined the use of machine learning to predict urban flood susceptibility in a tropical catchment area, specifically focusing on the southeastern region of Nigeria, which has been severely affected by floods due to climate change. The study emphasizes the importance of accurate forecasting and intervention strategies for effective flood mitigation. By analyzing regional hydrogeological data from 1981 to 2019 and processing remote sensing datasets from NASA and MERRA, the author developed an ARIMA model to forecast flooding patterns. This research aims to support regional agencies in adapting to flood challenges and assessing hydrologic extremes. Noymanee and Theeramunkong [34] investigated flood forecasting using machine learning techniques to enhance hydrological modeling in Thailand, where urban flooding is


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a significant concern. The study highlights the need for real-time flood level predictions, as existing early warning systems often suffer from inaccuracies. To improve predictions, the authors integrated five machine learning methods—linear regression, neural network regression, Bayesian linear regression, and boosted decision tree regression—into the MIKE-11 hydrologic forecasting model developed by the Danish Hydraulic Institute. This research aims to provide more reliable flood predictions, contributing to better flood management strategies in urban areas.

Sediment transport is crucial for river ecosystems, replenishing nutrients and supporting aquatic habitats. Accurate prediction of sediment transport is essential for various applications, including flood forecasting and water supply planning. While traditional process-driven models face validation challenges, data-driven models, particularly those leveraging AI techniques like machine learning (ML) and deep learning, offer promising alternatives. These recent advancements aim to develop more robust models that can effectively address the complexities of sediment transport. Goldstein et al. [14] conducted a review of machine learning applications in coastal sediment transport and morphodynamics. The study explored how machine learning (ML) techniques can extract insights from complex datasets, focusing on supervised regression tasks. The authors analyzed the scientific problems addressed by ML, the insights gained, and the motivations for employing these methods. Their findings reveal a wide range of research questions, from small-scale sediment transport predictions to larger-scale analyses of sand bar morphodynamics and coastal overwash. They highlight the advantages of using ML, such as improved predictability, model emulation, and the ability to incorporate uncertainty. The review also outlines best practices for coastal researchers utilizing ML and suggests future research directions, including the application of novel ML techniques and the utilization of increasingly available open data.

Afan [3] reviewed the development of artificial intelligence models for sediment transport prediction, highlighting the evolution and prospects of these technologies. Building on this foundation, Khan et al. [22] assessed soft computing techniques for estimating suspended sediment loads in rivers, while Zounemat-Kermani et al. [51] examined the complexities of sediment load modeling using integrative machine learning, focusing on the Loíza River in Puerto Rico. Expanding this research, Lund et al. [30] utilized machine learning to improve predictions of fluvial sediment transport, crucial for addressing environmental issues such as flooding and habitat degradation. They developed extreme gradient boosting models using data from the U.S. Geological Survey in Minnesota, analyzing around 400 watershed and streamflow features and narrowing them to 30 key variables. Their findings underscored the importance of watershed and catchment characteristics in enhancing prediction accuracy. Together, these studies demonstrate the significant potential of machine learning in sediment transport modeling, offering valuable insights for effective water and landscape management.

### 1.4. Category 4: assessing the impact of climate change, drought monitoring and management

Environmental challenges like climate change and ecosystem destruction pose significant threats to humanity and the planet, necessitating sustainable resource management and enhanced efficiency. Artificial intelligence (AI) and machine learning (ML) technologies present promising solutions by leveraging weather and hydrological data to forecast drought conditions and inform effective management strategies. Machine learning techniques have been increasingly applied to drought monitoring. Zhang et al. [49] employed the gradient boosting machine (GBM) and the extreme randomized tree (ERT) algorithm for nationwide drought assessment in China. Kaur et al. [23] utilized artificial neural networks (ANN), support vector machines (SVM), and random forests (RF) to predict drought. Hanadé Houmma et al. [18] integrated the vegetation condition index (VCI), the temperature condition index (TCI), and other remote sensing indices for drought monitoring. While machine learning has enhanced data mining and prediction accuracy compared to traditional methods, the growing volume of remote sensing data and complex drought factors present challenges for extracting comprehensive information. Park et al. [37] used machine learning to assess drought by integrating multi-sensor indices from MODIS and TRMM. They analyzed meteorological and agricultural drought during 2000-2012, employing random forest, boosted regression trees, and Cubist. Land surface factors (LST, ET) proved more significant for short-term drought, while vegetation indicators (NDVI, NMDI) were crucial for long-term assessment. This study demonstrates the effectiveness of machine learning in enhancing drought monitoring and assessment. Han et al. [17] developed a novel combined drought monitoring index (CDMI) using multi-sensor remote sensing data and machine learning. Recognizing the complex interactions among precipitation, temperature, evapotranspiration, and vegetation, they employed random forest analysis. The CDMI effectively monitored drought conditions in Shaanxi Province, demonstrating strong correlations with SPI and RSM compared to other indices. This study highlights machine learning's potential for developing effective drought monitoring tools without a deep understanding of causal mechanisms.

To summarize, the integration of artificial intelligence (AI) and machine learning (ML) applications is crucial for optimizing water treatment and quality monitoring, enhancing water consumption tracking, and improving water allocation strategies. These technologies play a significant role in groundwater management, river engineering, and flood management, particularly in the context of climate change. They facilitate effective drought monitoring and management by analyzing complex datasets and identifying patterns that traditional methods may overlook. While AI and ML offer substantial benefits, such as increased predictive accuracy and automation, challenges remain, including data quality concerns and the need for extensive computational resources. Addressing these drawbacks is essential for maximizing the potential of AI and ML in water resource management. By reviewing previous studies, it becomes evident that there is a lack of fundamental research on artificial intelligence (AI) and machine learning (ML) in hydraulic and water resources engineering, highlighting both challenges and opportunities. Therefore, conducting a comprehensive study to investigate the key challenges of AI, the role of AI in addressing water shortages and access to clean water, and considerations for using AI in water management is crucial. Such a study would significantly enhance our understanding of AI and ML performance and help optimize the design, operation, and management of hydraulic and water resource systems. This investigation complements prior research and aims to deepen our understanding of the challenges and opportunities presented by AI and ML. Ultimately, this research addresses a vital aspect of how AI and ML can serve as promising tools for water resource management, offering numerous potential benefits, including more accurate predictions of water availability, enhanced management of water infrastructure, and improved water quality monitoring, thereby contributing significantly to global efforts to combat water scarcity.

## 2. Opportunities and challenges of artificial intelligence

As water scarcity, climate change, and environmental concerns escalate, hydraulic and water resources engineering is crucial for ensuring efficient water management. With growing water challenges, AI technologies offer essential tools for process optimization and informed decision-making. The application of artificial intelligence (AI) and machine learning (ML) in water resource management presents a transformative opportunity to enhance efficiency, accuracy, and sustainability across various domains. From improving water treatment and quality monitoring to enabling precise water allocation and flood management, the potential benefits of AI are vast. However, the implementation of AI in various facets of hydraulic engineering and water resources management encounters several challenges. Understanding these obstacles and developing effective solutions is essential to harness the full potential of AI in promoting efficient water resource management. This section discusses various studies on the opportunities and challenges of AI in hydraulic engineering and water resources management. A general summary of these findings is then categorized.

Xie et al. [46] enhanced real-time prediction of effluent water quality in wastewater treatment plants (WWTPs) by developing a machine learning model that combines an improved feedforward neural network (IFFNN) with an optimization algorithm. This hybrid approach effectively simplifies wastewater treatment modeling and improves predictive accuracy but faces limitations, such as reliance on controlled laboratory data and the inability to incorporate historical effluent inputs. The authors emphasized the need for adaptive neural networks to address real-world complexities. Ray et al. [38] reviewed the transformative role of artificial intelligence (AI) in water treatment and seawater desalination, highlighting its ability to enhance data processing, optimization, and decision-making. They noted advantages like improved efficiency and cost-effectiveness but also pointed out challenges regarding data reliability and the absence of comprehensive processing guidelines, indicating a need for clearer frameworks. Osman et al. [35] focused on machine learning's application in enhancing membrane efficiency for processes like reverse osmosis. They noted significant advancements in pollutant removal and the use of optical coherence tomography for monitoring fouling. However, they acknowledged limitations in continuous monitoring and suggested that deep neural network models could improve predictive insights. Abba [1] developed an evolutionary data intelligence model to predict the performance of the Tamburawa water treatment plants in Nigeria. They emphasized the advantages of data-driven models, such as artificial neural networks (ANN) and support vector machines (SVM), but highlighted that no single modeling method fits all due to the complexity of hydro-environmental data. Lowe et al. [29] explored AI and ML applications in analyzing water quality data from diverse sources, noting their versatility in tasks like chlorination and membrane filtration. While these technologies can optimize processes, the authors identified challenges, including the need for reliable data and further development before real-world implementation.

Drogkoula [9] provided an overview of machine learning (ML) methodologies in water resource management, exploring how AI enhances data integration, decision-making, and sustainability. They noted ML's potential to improve efficiency but identified challenges such as data heterogeneity, the need for stakeholder education, high implementation costs, and issues with data quality. Additionally, the interpretability of ML models is a concern, particularly for supervised learning, which requires substantial labeled datasets. Nguyen et al. [33] evaluated the use of AI in forecasting the surface quality index of irrigation systems in the Red River Delta, Vietnam. They highlighted the advantages of machine learning and deep learning in managing nonlinear water quality relationships and handling large datasets, although challenges related to data quality, historical data needs, and implementation complexity persist. Goap et al. [13] focused on optimizing water resource utilization in precision farming through ML algorithms. Their proposed open-source smart system integrates data from various sources—such as remote sensing and soil moisture sensors—to enhance irrigation decision-making and promote efficient water usage. Singh et al. [40] introduced an automated ML model for predicting groundwater levels, emphasizing its ability to optimize hyperparameters and select the best-performing algorithm. They noted that ML addresses the limitations of traditional numerical modeling and remote sensing, demonstrating versatility in predicting various aspects of groundwater dynamics, including water quality indices and river flow.

Letessier et al. [28] introduced the Adaptive Structure of the Group Method of Data Handling (ASGMDH), a novel machine learning method designed to predict daily river flow rates using historical discharge data and real-time meteorological information. The study aimed to enhance prediction accuracy for applications like flood forecasting and irrigation planning. The advantages of ASGMDH include its ability to integrate diverse data sources and capture complex nonlinear relationships, outperforming traditional physical models. However, challenges such as extensive data preprocessing, parameter selection difficulties, and model interpretability were noted, along with the resource demands of traditional numerical models. Kumar et al. [26] examined challenges in flood prediction, focusing on data accessibility, ML model interpretability, and ethical considerations. They highlighted the advantages of AI and ML in processing high-dimensional and spatiotemporal data for improved predictions and early flood warnings. However, significant drawbacks include traditional models' struggles with nonlinear interactions, issues of overfitting in AI models, and the complexity of deep learning hindering interpretability. The authors stressed the need for future rese-


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arch to enhance the robustness of AI and ML applications in flood prediction. Huu Duy et al. [19] developed a theoretical framework combining machine learning, hydrodynamic modeling, and the analytic hierarchy process to assess flood risk downstream of the Ba River in Phu Yen. This approach allows for analyzing complex data from various sources, enabling accurate predictions of high-risk areas while automating the analysis process. However, the lack of universal guidelines for selecting appropriate machine learning algorithms for different regions and the reliance on high-quality data present challenges.

Wang and Chen [44] evaluated the application of ML in reservoir engineering, highlighting its potential to enhance accuracy and efficiency in tasks such as production prediction and reservoir characterization. Key advantages include the ability to process large datasets and automate tasks, although challenges remain. The authors noted difficulties in handling multiple data formats, reliance on high-quality data, and a lack of integration with physical laws, which can hinder model generalization and interpretability. They called for further research to enhance ML effectiveness in this field. Latif et al. [27] focused on sediment load prediction in the Johor River, comparing deep learning and ML models. They emphasized that AI algorithms can bypass complex physical processes and adapt through self-learning, making them efficient for time series forecasting. However, the study also pointed out significant drawbacks, such as the potential inadequacies of search techniques and concerns regarding the reliability of black box models in capturing long-term dependencies in historical datasets.

Nandgude et al. [32] emphasized the importance of extensive datasets, appropriate model selection, and computing resources for effective drought prediction. They noted that ML and deep learning techniques can identify drought impacts more efficiently than traditional methods, improving response times. However, challenges such as data unavailability and the variable performance of artificial neural networks (ANNs) were also highlighted. Mardian et al. [31] evaluated a machine-learning framework for the Canadian Drought Monitor (CDM), aiming to automate drought impact monitoring without ground support, especially in data-limited regions. Their approach benefits from learning relationships from training data and effectively utilizing big data, though it faces challenges related to data quality and the need for extensive training datasets. Zhang et al. [48] developed an integrated drought monitoring model using deep learning algorithms, which can extract valuable features from various drought factors, enhancing effectiveness. However, they also pointed out the necessity for substantial data and computational resources, which complicates implementation. Together, these studies underscore both the potential and challenges of using AI and ML in drought prediction and management. They stated further research is needed to address these limitations and fully leverage machine learning for effective drought monitoring. Shen and Lawson [41] explored the applications of deep learning (DL) in hydrology. Deep learning has transitioned from a niche tool to a preferred method for various prediction tasks, offering capabilities akin to traditional hydrologic models, including dynamical modeling and forecasting. Long short-term memory (LSTM) networks have demonstrated exceptional performance in capturing data dynamics, often surpassing traditional models, even in small-data scenarios, though caution is advised for critical applications. In subsurface hydrology, physics-informed machine learning approaches have emerged, integrating physical equations into neural network designs to facilitate training with limited data. The authors suggest that a deeper integration of domain knowledge and machine learning could enhance both prediction accuracy and understanding in hydrology, despite the current scarcity of interpretive machine-learning applications in the field.

Following a review of several studies, an overview of the key opportunities that AI offers in optimizing water resources and the profound impact these technologies can have on ensuring sustainable water management is highlighted below.

- Water Supply and Distribution: Designing systems to efficiently deliver potable water to communities. This includes the management of pipelines, treatment facilities, and distribution networks.
- Wastewater Management: Engineering solutions for the treatment and disposal of wastewater to protect public health and the environment. This involves designing treatment plants and implementing advanced treatment technologies.
- Stormwater Management: Developing systems to manage runoff during rainfall events, preventing flooding and water pollution. This includes green infrastructure solutions such as permeable pavements and retention basins.
- Irrigation Engineering: Designing irrigation systems that maximize agricultural productivity while minimizing water waste. This involves the use of modern technologies such as drip irrigation and automated control systems.
- Hydrology: Studying the movement, distribution, and quality of water in the environment. This includes modeling hydrological processes to predict water availability and assess flood risks.
- Data-Driven Decision Making: Utilizing AI algorithms to analyze large datasets to inform management decisions, improve predictive accuracy, and optimize resource allocation.
- Real-Time Monitoring: Implementing sensor networks and IoT technologies that provide real-time data on water quality and quantity, enabling proactive management responses.
- Predictive Modeling: Developing advanced models that simulate water system behavior under various scenarios, helping engineers design more resilient infrastructure and respond effectively to changing conditions.
- Automation and Control: Employing AI-driven automation in water treatment and distribution systems to enhance efficiency, reduce operational costs, and minimize human error.
- Infrastructure Optimization: Applying AI to optimize the design and maintenance of river infrastructures, such as levees and dams, enhancing their resilience to extreme weather events.
- Demand Forecasting: Leveraging machine learning algorithms to analyze historical consumption patterns and predict future water demand more accurately.
- Smart Water Management: Implementing IoT devices and

AI analytics to optimize water distribution networks, minimizing losses and ensuring equitable allocation.
- User Behavior Analysis: Utilizing AI to analyze consumer behavior patterns, enabling targeted interventions to promote water conservation among users.

On the other hand, some major challenges and their solutions are highlighted. These include a clear description of the challenges of artificial intelligence (AI) in various areas of water resource management, including optimizing water treatment, monitoring, and managing resources effectively.

- Data Quality: Data quality is crucial for AI model performance. Inaccurate or incomplete data can compromise prediction reliability. Implementing robust data cleaning and validation protocols is essential to ensure data quality and optimize AI model training. Also, Accurate predictions require high-resolution data, which can be limited. Collaborative data sharing among agencies and stakeholders can improve data availability and enhance modeling accuracy.
- Data Accessibility: Comprehensive dataset accessibility can be a challenge, especially in under-monitored regions. Investing in advanced monitoring technologies (e.g., IoT sensors) can enhance data availability and provide real-time insights.
- Integration of Data Sources: Integrating data from diverse sources (sensors, lab tests) can be challenging due to differing formats and standards. Establishing standardized formats and protocols for data collection can streamline data integration and enhance the effectiveness of AI and ML applications.
- Non-stationarity, or changing data patterns over time, poses significant challenges for AI models in dynamic fields like hydrology. Climate change, land use changes, and evolving environmental conditions contribute to non-stationarity. To address these challenges, incorporating domain knowledge into AI model development is crucial. By integrating physical principles and process understanding, practitioners can enhance model robustness, improve predictive accuracy, and make informed decisions in changing environments.
- Model Interpretability and Expanding: AI models can often be indistinct, making it difficult to understand their decision-making processes. This lack of transparency can hinder regulatory compliance. Explainable AI techniques can address this by improving model interpretability, fostering stakeholder trust, and ensuring compliance. Also, AI models trained on specific datasets may face challenges when applied to new regions or conditions. Transfer learning techniques can help address this by adapting models to perform well in different contexts. Furthermore, The complexity of phenomena arises from the interplay of numerous variables. Multi-scale modeling approaches can help capture these interactions and improve predictive accuracy.
- Adaptability of Models: AI models must adapt to changing conditions. Continuous learning systems can enable models to learn from new data and evolve, ensuring long-term reliability.
- Stationarity Of Models: Non-stationarity, or changing data patterns over time, poses significant challenges for AI models in dynamic fields like hydrology. Climate change, land use changes, and evolving environmental conditions contribute to non-stationarity. To address these challenges, incorporating domain knowledge into AI model development is crucial. By integrating physical principles and process understanding, practitioners can enhance model robustness, improve predictive accuracy, and make informed decisions in changing environments.
- Cost: Real-time management requires efficient data processing, which can be computationally demanding. Cloud computing solutions offer the necessary processing power to enable real-time data analysis. Also, Developing and implementing AI systems can be expensive, especially when considering the costs of data acquisition, system integration, and ongoing maintenance.
- Long-Term Data Needs: Long-term data is crucial for effective assessments, but availability can be inconsistent across regions. Centralized repositories for historical data can improve accessibility and support research and model training.
- Inherent complexity of water systems: Water systems are complex, and influenced by both natural and human factors. This complexity hinders the development of accurate models, leading to potentially ineffective management solutions. Addressing this requires integrated models that consider hydrological, ecological, and socioeconomic components. Collaboration among scientists, policymakers, and communities is crucial for sharing knowledge and data. Investing in training programs can enhance stakeholder understanding of water systems and improve model input and interpretation.

While AI and ML hold great promise for advancing water resource management, overcoming the associated challenges is crucial for effective implementation. By addressing issues related to data quality, accessibility, model interpretability, and computational demands, stakeholders can maximize the benefits of AI technologies. Implementing the proposed solutions can foster a more sustainable approach to managing water resources, ultimately contributing to global efforts in combating water scarcity and ensuring clean water access for all.

## 3. Considerations of using artificial intelligence

Firrstly, data quality is paramount in artificial intelligence. High-quality data enhances model performance, accuracy, and reliability, fostering trust and confidence. Addressing biases within data is crucial to prevent their perpetuation in AI-generated outputs. Diverse and representative datasets improve an AI model's ability to generalize across various contexts, ensuring its relevance and effectiveness. Data maintaining quality is essential for realizing AI's full potential, driving innovation, and ensuring ethical outcomes. The question is what are the key components of quality data in AI?

Data quality is a cornerstone of AI success. Accurate, consistent, complete, and timely data ensures reliable AI outcomes. Errors in data can lead to incorrect decisions, while inconsistent for-


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mats hinder efficient processing. Incomplete data limits pattern recognition, and outdated data may not reflect current trends. Relevance is key, as irrelevant data can clutter models and reduce efficiency. By prioritizing data quality, organizations can optimize AI performance, foster trust, and avoid potential pitfalls. Data governance, tools, and team collaboration are essential for ensuring data quality in AI. A robust data governance framework, data quality tools, and a dedicated team can create a culture of data quality and ensure consistent access to high-quality data. Collaborating with data providers and continuously monitoring data quality metrics can further minimize risks and optimize AI performance.

Data processing, secondly, is a critical component of any AI application. Once relevant data is gathered from diverse sources, effective data processing must be applied. Data preprocessing—cleaning, normalizing, and transforming data—is essential for preparing the dataset for modeling. Following preprocessing, data exploration and analysis are conducted to understand distributions, patterns, and relationships using visualization and statistical techniques. The dataset is then divided into training, validation, and testing sets to support model development and evaluation. Additionally, data augmentation techniques, such as image rotation or noise addition, can be employed to enhance data variety. By carefully addressing these data processing steps, organizations can ensure their AI models are trained on high-quality data, resulting in more accurate and reliable outcomes.

Thirdly, choosing the reliable AI model is crucial for success in today's fast-paced environment, as it significantly impacts performance, accuracy, and adaptability in real-world applications. Effective model selection is key to successful AI implementation. Practitioners must consider the type of problem, resource constraints, the need for interpretability, and the characteristics of the available data. By understanding these factors, they can develop systems that are accurate, efficient, and adaptable, unlocking AI's full potential. Moreover, AI systems should be designed to adapt to new data, evolving scenarios, and changes in their operating environment. This adaptability is vital for maintaining performance and relevance over time. Scalability is also essential, especially for larger projects, as it enables systems to manage increased data volumes and complexity without sacrificing efficiency. By prioritizing both adaptability and scalability, AI practitioners can create robust systems that excel in dynamic environments.

After selecting the appropriate AI model, evaluating its performance using the right metrics is crucial. Choosing suitable evaluation metrics—such as accuracy, precision, and recall—helps assess model effectiveness and determine its impact. Establishing clear performance metrics is essential for making necessary adjustments and improvements. Continuous monitoring is also vital, as ongoing assessment ensures that AI models remain effective as new data and conditions emerge. AI tools can sometimes produce outputs that are nonsensical or inaccurate, often referred to as „AI hallucinations." Therefore, it is important for researchers and users to independently verify the accuracy of the outputs generated by AI systems, rather than relying solely on them. This approach promotes reliability and confidence in AI-generated results.

In addition, when developing machine learning models, particularly in dynamic fields like hydrology, it is crucial to consider the challenges posed by non-stationarity. Non-stationarity refers to the changing statistical properties of a process over time, influenced by factors such as climate change, land use alterations, and evolving environmental conditions. This variability can significantly undermine the reliability of AI models, which often depend on historical data for predictions. As underlying data patterns shift, models trained on past data may struggle to deliver accurate forecasts, leading to potentially poor decision-making. To effectively address these challenges, it is essential to incorporate a robust understanding of the underlying processes into model development. By integrating domain knowledge, practitioners can impose better constraints on AI models, allowing them to adapt to variations in the data. Emphasizing physical principles and process understanding can enhance model robustness, improve predictive accuracy, and facilitate informed decision-making in the face of changing conditions. This approach not only aids in adapting to non-stationary environments but also promotes a more comprehensive understanding of the systems being modeled, ultimately leading to more effective applications of machine learning.

Environmental considerations, also, are crucial when implementing artificial intelligence (AI) in water management, as its use can lead to significant ecological consequences if not approached sustainably. While AI has the potential to optimize water consumption, improper management may result in excessive extraction or pollution of water resources, causing negative environmental impacts. Key aspects of environmental considerations include sustainable implementation, energy consumption, and impact on biodiversity, as well as long-term effects. Sustainable implementation is vital; AI solutions must be designed to prevent over-extraction of water resources that can harm ecosystems. Additionally, AI algorithms, especially those requiring substantial computational power, can consume significant amounts of energy, potentially increasing the carbon footprint of water management practices. Poorly managed AI applications may also disrupt local habitats or threaten species by altering water availability and quality. While AI can provide short-term optimizations, it is essential to consider its long-term ecological impacts to ensure sustainable water management practices. To minimize the environmental footprint of AI in water resources management, several strategies can be adopted, including utilizing renewable energy, optimizing algorithm efficiency, implementing resource-efficient practices, monitoring environmental impacts, promoting green computing, and supporting ecosystem health. By integrating these strategies, AI can be harnessed for more sustainable and effective water resource management.

Furthermore, regulatory compliance is critical when implementing AI systems. These systems must adhere to legal regulations and industry standards, particularly concerning data protection and safety. Ensuring compliance mitigates legal risks and fosters trust among users and stakeholders. By integrating compliance considerations into the development and deployment of AI, organizations can safeguard sensitive information and maintain ethical standards, thereby promoting responsible and sustainable AI use.

Moreover, both ethical and social considerations must be addressed in the use of artificial intelligence in water management. The collection and analysis of sensitive water consumption data raise important privacy and security concerns, making it essential to establish appropriate ethical guidelines to protect the rights of individuals and communities. Key ethical considerations include privacy, informed consent, data security, transparency, equity, accuracy, integrity, environmental impact, and regulatory compliance. In addition to ethical concerns, the implementation of AI in water management can have significant social impacts, particularly regarding job displacement. AI may automate tasks previously performed by human workers, potentially leading to job losses and an increased need for reskilling and retraining. To mitigate these negative effects, it is crucial to develop reskilling programs that assist affected workers in transitioning to new roles in emerging fields. These programs should provide training and support for acquiring skills in high-demand areas such as data analysis, programming, and AI development. Collaboration among governments, organizations, and educational institutions is vital to ensure these programs are accessible and inclusive for all workers.

## 4. Optimization techniques based on artificial intelligence

Artificial intelligence-based optimization techniques for water resources management involve utilizing machine learning and other AI algorithms to analyze and optimize the allocation and distribution of water within a system. These techniques enhance the efficiency of water management, reduce waste, and ensure that water resources are managed in an environmentally sustainable manner. Some key techniques in water resource management include [2, 16, 36, 42]:

- Machine learning algorithms are employed to create predictive models that forecast water demand and optimize the allocation and distribution of water resources.
- Deep learning techniques, such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), are used to analyze large datasets and make predictions about water consumption and distribution.
- Genetic algorithms optimize water allocation and distribution by generating a set of rules that guide decision-making processes, ensuring efficient resource management.
- Reinforcement learning involves using machine learning algorithms to learn from experience, improving decision-making capabilities over time as the system adapts to new data and scenarios.
- Multi-objective optimization techniques are used to balance conflicting objectives, such as maximizing water availability while minimizing environmental impacts. These methods help in finding the best possible solutions that address multiple goals simultaneously.
- Real-time monitoring and decision-making involve using AI-based techniques to continuously monitor water consumption and distribution. This real-time data allows for rapid decision-making and optimization, ensuring that water management practices are both efficient and responsive to changing conditions.
- Decision Trees are a widely-used machine learning algorithm for solving classification and regression problems, especially in allocation and optimization. In water distribution, decision trees can identify the most critical factors influencing the allocation and distribution of water resources. This analysis can inform the development of decision support systems, enabling water managers to make more informed decisions about allocating and distributing water resources efficiently.
- Support Vector Machines (SVMs) are a popular machine learning algorithm used for solving classification and regression problems in optimizing water allocation and distribution. SVMs can predict water demand based on various factors such as population, climate, and land use. This information can then be used to optimize the allocation and distribution of water resources in a specific area.
- Artificial Neural Networks (ANNs) are a widely-used machine learning algorithm inspired by the structure and function of the human brain. In the context of optimizing water allocation and distribution, ANNs can predict water demand based on factors like population, climate, and land use. This information can then be utilized to optimize the allocation and distribution of water resources within a particular area.
- The K-Nearest Neighbors (KNN) algorithm is a simple yet powerful machine learning technique used to solve classification and regression problems in optimizing water allocation and distribution. KNN can predict water demand based on various factors such as climate, population, and land use. This information can then be used to optimize the allocation and distribution of water resources within a specific area.
- Clustering is a machine learning technique used to group similar data points, which is particularly useful in the allocation and optimization of water distribution. By clustering areas with similar water demand patterns, this information can be used to optimize the allocation and distribution of water resources across different regions.

## 5. Conclusions

In recent years, the rise of artificial intelligence (AI) has established it as a vital technology in hydraulic and water resources engineering, especially as urbanization and population growth intensify water demand. AI offers transformative solutions across various applications, including optimizing water treatment processes, monitoring water quality, tracking consumption, managing groundwater resources, and addressing hydrological challenges like climate change. While the integration of AI and machine learning (ML) in water resource management presents significant opportunities for enhancing efficiency, accuracy, and sustainability, it also faces various challenges that must be understood and addressed. Developing effective solutions to these obstacles is crucial for fully leveraging AI's potential to improve water resource management practices. This essay emphasizes the transformative potential of integrating artificial intelligence (AI) into hydraulic and water resource management, particularly in optimizing water distribution. By accurately simulating water behavior and predicting essential parameters, such as pressure and flow, AI enhances traditional models that depend on extensive data and computational resources. Its applications extend to managing water quality, forecasting floods, simulating groundwater dynamics, improving irrigation practices, detecting leaks, and optimizing desalination processes. However, several


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challenges must be addressed. Data quality is crucial for AI model success, as inaccuracies can undermine prediction reliability. Establishing robust data cleaning and validation protocols, along with fostering collaboration among stakeholders, is essential to enhance data availability and modeling accuracy. In under-monitored areas, advanced technologies like IoT sensors can provide real-time insights, while standardized data collection protocols facilitate the integration of diverse sources. The dynamic nature of hydrology, shaped by factors like climate change, requires incorporating domain knowledge into AI model development for improved adaptability. While AI and machine learning (ML) offer significant potential for enhancing water resource management, it is essential to overcome the associated challenges for effective implementation. By addressing these challenges, stakeholders can fully maximize the benefits of AI technologies. Implementing the proposed solutions will promote a more sustainable approach to managing water resources, ultimately contributing to global efforts to combat water scarcity and ensure access to clean water for all.

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