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The latest innovative avenues for the utilization of artificial Intelligence and big data analytics in water resource management

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ABSTRACT

The effective management of water resources is essential to environmental stewardship and sustainable development. Traditional approaches to water resource management (WRM) struggle with real-time data acquisition, effective data analysis, and intelligent decision-making. To address these challenges, innovative solutions are required. Artificial Intelligence (AI) and Big Data Analytics (BDA) are at the forefront and have the potential to revolutionize the way water resources are managed. This paper reviews the current applications of AI and BDA in WRM, highlighting their capacity to overcome existing limitations. It includes the investigation of AI technologies, such as machine learning and deep learning, and their diverse applications to water quality monitoring, water allocation, and water demand forecasting. In addition, the review explores the role of BDA in the management of water resources, elaborating on the various data sources that can be used, such as remote sensing, IoT devices, and social media. In conclusion, the study synthesizes key insights and outlines prospective directions for leveraging AI and BDA for optimal water resource allocation.

1. Introduction

Effective management of water resources plays a vital role in ensuring their availability and quality for human and environmental needs [1]. Managing water resources effectively is critical to promoting sustainable development, reducing water-related conflicts, and protecting water ecosystems. It involves the efficient use of water resources and the protection of water resources from degradation, pollution, and overuse [2].

The management of water resources is a complex and challenging task, which requires to integrate different disciplines and consider a wide range of factors, including water quality and quantity, environmental impacts, social and economic factors, and climate change [3]. A number of obstacles have hindered the efficacy of conventional

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approaches to water resource management (WRM). For instance, rapid population growth and urbanization raise the demand for urban water resources. Conventional systems frequently struggle to meet this increased demand, resulting in water scarcity and quality problems. Moreover, changing climate patterns, such as altered precipitation and an increase in the frequency of extreme weather events, disrupt the predictability of water supply. Traditional management techniques may not be able to handle the resulting uncertainty. In addition, ineffective land management can result in several issues, including soil erosion, deforestation, and the disappearance of wetlands. These ecosystems play a vital role in moderating the flow and quality of water, and their degradation can exacerbate inundation and diminish water storage capacity. Furthermore, water pollution is caused by industrial discharges, agricultural effluent, inadequate wastewater treatment, etc [4,5]. Managing and mitigating the negative effects of contaminants on water quality is typically difficult with conventional methods [6]. Ineffective agricultural practices and obsolete irrigation techniques result in excessive water loss [7,8]. Conventional approaches neither adequately promote water conservation practises nor incentivize the adoption of new technologies. Various sectors such as agriculture, industry, and municipalities frequently manage water resources independently. This fragmented approach can lead to resource allocation conflicts and hinder overall sustainability. Moreover, numerous water supply and distribution systems are obsolete and insufficient to meet contemporary demands. Maintaining and modernizing this infrastructure necessitates substantial expenditures, which can strain traditional management budgets. Effective water managemet requires the participation of numerous stakeholders, such as local communities, governments, industries, and environmental organizations. It is possible that conventional methods do not prioritize inclusive decision-making processes.

Moreover, management of water requires traversing intricate legal and regulatory frameworks. Outdated or contradictory regulations can impede the implementation of adaptive management strategies and innovative solutions. Accurate information on water availability, quality, and consumption is essential for making informed decisions. For an effective management, conventional approaches may lack comprehensive monitoring systems that provide real-time data. More importantly, because of contending budget priorities, conventional strategies may encounter financial constraints. Limited financial resources can impede investment in cutting-edge technologies and infrastructure upgrades.

In response to these challenges, new and innovative approaches to WRM are needed. Artificial Intelligence (AI) and Big Data Analytics (BDA) offer significant potential to improve it by providing real-time data, efficient data analysis, and data-driven decision-making [9]. These technologies have the potential to transform the way WRM is performed and support the development of sustainable and effective water management practices [10].

AI provides real-time monitoring and analysis of water resources, which can support data-driven decision-making and optimization of water allocation and demand forecasting [11]. For example, machine learning algorithms can be used to predict water quality and allocate water resources based on real-time data [12]. Deep learning algorithms can be used to analyze vast amounts of data collected from various sources to identify trends, patterns, and potential risks in WRM [13]. BDA provides new insights into WRM by leveraging the vast amounts of data generated by and gathered from various sources, such as remote sensing, Internet of Things (IoT) devices, and social media [14]. BDA can be used to support WRM by improving the accuracy and efficiency of data analysis, identifying new data sources, and providing new insights into this issue [15]. The integration of AI and BDA into WRM can support sustainable and effective practices, promote water security, and protect water ecosystems. The utilization of these technologies has the potential to transform the way WRM is performed and provide innovative solutions to the challenges that may appear in this domain [16].

The purpose of this review is to spotlight the latest innovative avenues for the utilization of AI and BDA in WRM. The review will cover various AI technologies applicable to this domain, such as machine learning and deep learning, and different applications of AI in this regard, such as water quality monitoring, water allocation, and water demand forecasting. The review will also discuss the utilization of BDA in WRM, including different data sources that can be leveraged and the potential benefits and limitations of these innovations. The review will comprehensively review the current state-of-the-art approaches to utilizing AI and BDA in WRM and highlight the future directions for research and implementation. The next section discusses the main challenges in the WRM process.

2. Challenges arising to water resource management

2.1. *An overview*

Management of water resources is a multifaceted endeavor, which requires careful consideration of numerous environmental, social, and economic factors [16]. However, conventional approaches to WRM face a number of obstacles to their effectiveness and viability. This section discusses the current obstacles encountered by these approaches, emphasizing the complexity of managing this essential resource.

2.1.1. *Growth of population and urbanization*

The world's population is expanding swiftly, with a significant portion of this growth occurring in urban areas. This transition in population increases the demand for water resources to sustain domestic industrial and agricultural activities. Conventional systems of water management, which have been designed for regions with a low population density, struggle to meet this rising demand [2]. As a consequence, urban centers frequently experience water scarcity, excessive exploitation of groundwater, and increased competition between sectors for limited water resources.

2.1.2. *Climate change*

WRM now faces unprecedented levels of uncertainty because of climate change. Changing precipitation patterns, an increase in the frequency of droughts and flooding, and rising temperatures impede the ability to predict water availability. In the face of these swiftly altering conditions, conventional management practices based on historical data and suppositions may prove inadequate. This difficulty necessitates the development of adaptive management strategies that can respond dynamically to the patterns of climate change [17,18].

2.1.3. *Ecosystem degradation*

Ecosystems play a crucial role in regulating the quantity and quality of water. Nonetheless, human activities such as deforestation, urban expansion, and unsustainable agricultural practices have contributed to the degradation of these ecosystems. This degradation disrupts natural water flow patterns, reduces the capacity to store water, and increases the risk of inundation. The insufficient consideration of ecosystem services in conventional approaches to WRM frequently results in suboptimal outcomes for both humans and the environment [19].

2.1.4. *Water contamination*

Water contamination is caused by the discharge of pollutants from industrial processes, agricultural effluent, and inadequate sanitation systems. The complex challenges presented by contaminated water sources are frequently neglected by conventional management approaches, which concentrate on water supply and distribution. Addressing water pollution necessitates integrating effluent treatment, pollution prevention measures, and stringent regulatory frameworks into comprehensive strategies [20,21].

2.1.5. *Wasteful water use*

Particularly in agriculture sector, inefficient water use exacerbates water scarcity problems. As a result of their lack of precision and optimization, the use of conventional irrigation techniques result in substantial water loss. Conventional management practices may struggle to promote the adoption of advanced irrigation technologies and water-efficient practices, thereby perpetuating unsustainable patterns of water consumption [8].

2.1.6. Absence of integrated administration

The interconnectedness and interdependence of water resources transcend sectoral boundaries. However, conventional approaches frequently compartmentalize water management, resulting in resource allocation conflicts and lost opportunities for synergy. Integrated WRM, which takes into account the holistic nature of water systems, is essential for attaining sustainable outcomes and harmonizing competing demands [19,22].

2.1.7. Outdated facilities

Numerous water supply and distribution systems were created decades ago and are ill-equipped to meet contemporary needs. A deteriorating infrastructure increases the likelihood of water leakage, inefficiencies, and service interruptions. Efforts made to improve system resiliency and efficiency are hindered by the inability of conventional management to secure funding for infrastructure enhancements [13,22].

2.1.8. Limited stakeholder participation

To manage water resources successfully, there is a need for the participation of a variety of stakeholders, each with their own perspectives and objectives. There may be a lack of inclusive decision-making processes that adequately account for local communities, industries, environmental organizations, and government agencies in conventional approaches. This can result in suboptimal solutions and heightened stakeholders tensions [8,23].

2.1.9. Legal and compliance obstacles

The complex web of water-related regulations and legal frameworks is a formidable obstacle to overcome the obstacles to managing water resources. Ineffective strategies can be impeded by outmoded laws, contradictory regulations, and jurisdictional ambiguity. The inability of conventional approaches to adapt to changing legal landscapes may impede progress and innovation [2].

2.1.10. Absence of data and tracking

To make informed decision in WRM, accurate and current data are indispensable. There may be a lack of comprehensive monitoring systems that provide real-time data on water availability, quality, and usage in conventional approaches. Inadequate data can lead to suboptimal resource allocation and a diminished capacity to address emergent challenges [8].

2.1.11. Economic pressures and limited resources

WRM is frequently hampered by budgetary constraints and competing priorities. Investments in infrastructure enhancements, cutting-edge technologies, and capacity development may be hampered by insufficient financial resources. This difficulty highlights the need for innovative financing mechanisms and cost-effective solutions to guarantee the sustainability of water resources.

2.1.12. Hydro-energy challenges

Hydro-energy, derived from the movement of water in rivers and structures, plays a crucial role in the generation of global energy [24]. However, the incorporation of Hydro-energy into WRM presents numerous complex obstacles. This section explores the unique complexities of hydro-energy within the context of WRM as a whole.

Hydro-energy projects, such as dams and reservoirs, frequently modify rivers' ecosystems and water flow patterns. These modifications can disrupt aquatic habitats, have an effect on fish migration, and diminish sediment transport downstream. Ensuring the sustainability of water management practices requires striking a balance between the energy potential of Hydro-energy and the preservation of ecosystem health [17].

Consistent water flow is required for hydroelectric power generation. This can result in conflicts between agriculture, industry, and municipal water supply. To determine equitable water allocation between energy production and other sectors, particularly during water-scarce periods, there is a need for robust regulatory frameworks and preparing the stage for effective stakeholders' engagement [25].

Seasonal variation and alterations in precipitation patterns have an effect on Hydro-energy production. The introduction of uncertainty by climate change modifies the timing and availability of water resources. Fluctuations in river flow and reservoir levels can impact energy production, necessitating adaptive strategies to mitigate disruptions [24].

Dams and reservoirs contain sediment, resulting in erosion downstream, decreased sediment delivery, and altered sediment transport dynamics. This has an effect on river morphology, aquatic habitats, and ecosystems dependent on sediment. It is essential to implement effective strategies for sediment management to preserve both energy production and ecological integrity [25].

Infrastructure for Hydro-energy, such as dams and turbines, must be routinely maintained to ensure safe and efficient operation. Aged infrastructure is susceptible to deterioration, which may result in safety hazards and operational interruptions. When resources are limited, balancing the need for maintenance with consistent energy production presents challenges.

Hydro-energy projects can result in the displacement of communities and the alteration of local cultures and ways of life. Creation of reservoirs and alterations to river patterns can have an effect on fisheries, agriculture, and traditional practices. To mitigate negative social impacts and ensure their participation in decision-making processes, it is essential to engage meaningfully with affected communities. The development of hydro-energy initiatives necessitates navigating complex regulatory procedures, environmental assessments, and permit requirements. Achieving a balance between energy requirements and environmental protection can result in protracted approval processes and potential conflicts among stakeholders with diverse interests. The downstream water quality can be impacted by reservoir sedimentation, altered flow patterns, and temperature fluctuations. Managing and mitigating potential adverse effects on water quality, aquatic life, and downstream water users require careful consideration and proactive actions [26].

At the conclusion of their useful lives, Hydro-energy facilities must be decommissioned appropriately. This procedure entails addressing potential environmental impacts, restoring river systems, and managing lingering infrastructure. To minimize long-term liabilities, it is crucial to plan for decommissioning from the start. Hydro-energy technology continues to develop, with an emphasis on maximizing efficiency, minimizing environmental impacts, and augmenting energy storage capacities. A proactive approach is required to integrate these innovations into existing infrastructure while addressing potential technical and financial obstacles. Hydro-energy is a renewable energy source, but its incorporation into water resource management presents a number of unique challenges. It is complex to balance the energy production with ecological, social, and regulatory considerations. To address these obstacles; energy developers, regulatory bodies, environmental agencies, and affected communities must collaborate to ensure a sustainable and equitable approach to the use of hydro-energy in the context of WRM as a whole.

2.2. Enhancing water resource management through AI and big data analytics

WRM has increasingly faced complex obstacles as a result of technological progress. The combination of AI and BDA has emerged as a game-changing strategy for optimizing water allocation, usage, and conservation [27]. This section describes how the synergy between AI and BDA can transform WRM by facilitating informed decision-making, proactive resource management, and sustainable outcomes.

2.2.1. Decision-making informed by data insights

AI and BDA provide WRM professionals with an abundance of data-driven insights. These technologies combine information from numerous sources, including remote sensing satellites, weather stations, and sensors, to provide a comprehensive understanding of water dynamics. Decision-makers obtain real-time information on water availability, quality, usage patterns, and ecosystem health by using sophisticated techniques of data analysis. This type of informed decision-making is essential for the development of strategies that effectively address water scarcity, pollution, and climate-induced variability [28].

2.2.2. The use of predictive models for efficient planning

Modern WRM is based on predictive modeling facilitated by AI. This type of modeling uses historical and real-time data to simulate a variety of scenarios, predicting the availability of water under varying climate conditions and human interventions. Predictive models aid in the development of responsive drought mitigation, flood management, and optimal reservoir operation strategies. By quantifying the potential outcomes of various decisions, planners can proactively adapt to changing conditions, thereby minimizing risks and optimizing resources [26,29].

2.2.3. Effectiveness of water allocation and conservation

It is essential to optimize water allocation in order to balance the needs of agriculture, industry, urban areas, and ecosystems. Algorithms powered by AI and fed with real-time data can dynamically adapt water distribution to changing conditions. In addition, these technologies can identify and correct inefficiencies in water use, for instance, by the detection of leaks in distribution networks and the application of precise irrigation in agriculture. This not only conserves water, but also increases the overall efficacy of water systems [7].

2.2.4. Systems for early warning of extreme events

Extreme weather events, such as floods and droughts, are capable of having devastating effects on water resources. Early warning systems powered by AI analyze meteorological and hydrological data to forecast potential disasters [30,31]. These systems provide significant lead time for implementing mitigation measures, evacuating vulnerable areas, and allocating emergency response resources. Using real-time data, decision-makers can improve community safety and mitigate the effects of extreme events on water supply and infrastructure.

2.2.5. Management and restoration of ecosystems

AI and BDA bolster ecosystem-based WRM approaches. Using remote sensing and data integration techniques, these technologies evaluate the health of aquatic and terrestrial ecosystems. These insights guide restoration efforts by identifying areas in need of intervention, evaluating the influence of restoration projects on water flow and quality, and tracking the long-term success of these initiatives. This unified strategy promotes both ecological health and sustainable water management [32].

2.2.6. Engagement with stakeholders and transparency

Engaging stakeholders is essential for WRM success. By providing accessible data platforms, AI and BDA facilitate transparent and inclusive decision-making processes. These platforms enable stakeholders, including communities, industries, and governments, to access real-time data and collaborate on resource management. This promotes confidence, reduces conflicts, and encourages participation in conservation efforts.

2.2.7. Adaptive strategies in confrontation with climate change

Climate change makes WRM more complicated. Climate modeling powered by AI forecasts changes in precipitation, temperature, and water availability. By incorporating these projections into management strategies, decision-makers can develop plans that are adaptable and resilient to shifting conditions. The iterative nature of AI enables continuous strategy refinement as new data become available [17,18].

2.2.8. Compliance and enforcement with regulations

By automating compliance surveillance, AI and BDA increase regulatory oversight. These technologies can detect illegal water usage, pollution incidents, and other violations rapidly. Large datasets are analyzed by machine learning algorithms to identify patterns of noncompliance, allowing authorities to take prompt enforcement actions, and deter future violations.

2.2.9. Drought management

AI and BDA can be used to support drought management by providing real-time data on water availability and usage. For example, AI algorithms can be used to analyze data on water usage and availability to determine the most efficient allocation of water resources during times of drought [33].

2.2.10. Flood management

AI and BDA can be used to support flood management by providing real-time data on water levels and flow rates. For example, AI algorithms can be used to analyze data from water level sensors and satellite imagery to predict and respond to potential floods [29].

These are just a few examples of how AI and BDA can be used in water resource management. The potential applications of AI and BDA in this field are vast, and there is a growing recognition of the need for new and innovative approaches to WRM to address the challenges faced with in this domain and support sustainable and effective water management practices [34]. The use of AI and BDA in WRM will help to ensure that water resources are managed in a sustainable and efficient manner [35].

3. Innovations in AI for water resource management

3.1. Different AI-based technologies applicable to water resource management

There are several types of AI technologies applicable to WRM, each with their own unique capabilities and limitations. In the following, a number of important examples are explained.

3.1.1. Machine learning

It is a type of AI that enables computers to learn from data and make predictions or decisions based on that learning. In the context of WRM, machine learning algorithms can be used to analyze data from water quality sensors, water infrastructure, and other sources to detect changes in water quality, predict water usage patterns, and improve decision-making processes [36].

3.1.2. Deep learning

It is a subset of AI, which has emerged as a potent technique for deciphering complex patterns and making accurate predictions from massive datasets. Deep Learning offers an innovative approach to addressing challenges associated with water availability, quality, distribution, and ecological health in the domain of WRM. This subsection discusses the concept of Deep Learning in WRM, detailing its prospective applications and advantages.

Deep Learning is an AI subfield inspired by the structure and function of the neural networks in the human brain. These networks comprise layers of artificial neurons, which process and transform data and are interconnected [37–39]. Deep Learning models, specifically CNNs and

RNNs, excel at identifying complex patterns in images, sequences, and time-series data [40,41].

Deep Learning algorithms are capable of analyzing large datasets of water quality parameters (e.g., temperature, pH, and contaminants) to detect pollution incidents and identify trends over time. Models can predict hazardous algal blooms, chemical contamination, and bacterial outbreaks, facilitating in the protection of public health through early intervention [42].

Additionally, Deep Learning can analyze historical and real-time data on rainfall, river levels, and topography to generate accurate flood prediction models. By identifying prospective flood-prone areas and anticipating extreme events, local authorities would be able to implement evacuation plans in a timely manner and deploy resources effectively.

In addition, Deep Learning models can process satellite imagery and climate data to monitor plant health and soil moisture levels during a drought. These insights aid in the early detection of drought, guiding efficient water allocation, cultivation planning, and WRM during periods of water scarcity [18].

Deep Learning algorithms can analyze patterns of water consumption in urban areas, taking into consideration variables such as weather, demographics, and economy. Accurate water demand forecasts allow utilities to optimize water distribution and plan infrastructure investments. Deep Learning techniques can improve hydrological models through the incorporation of large datasets from remote sensing, weather forecasts, and ground-based sensors [43]. These models enhance the knowledge of watershed dynamics, streamflow forecasts, and reservoir operations [15].

Deep Learning also excels at recognizing complex patterns in large datasets, uncovering insights that conventional methods may overlook. It can fuse disparate data sources such as satellite imagery, sensor measurements, and social media data to provide an all-encompassing view of water systems. Moreover, Deep Learning models can predict future water-related events with a higher degree of precision, facilitating proactive management strategies. Once trained, Deep Learning models can automate data analysis, which enables real-time decision making and reduces manual labor.

The involvement of Deep Learning in WRM is likely to increase as data availability and computational resources continue to grow. Researchers are striving to enhance the interpretability of models, resolve data limitations, and develop hybrid approaches that combine AI with conventional hydrological models. The incorporation of Deep Learning into WRM has the potential to facilitate more precise, expeditious, and proactive management of water resources, thereby contributing to a sustainable water future [44].

3.1.3. *Natural language processing (NLP)*

This is a type of AI that enables computers to understand and process the human language. In the context of WRM, NLP can be used to process unstructured data such as social media posts to monitor public opinions and attitudes toward WRM [45].

3.1.4. *Computer vision*

It is a type of AI that enables computers to process and understand images and videos. In the context of water resource management, computer vision can be used to analyze satellite imagery and other images to monitor changes in water availability, water usage, and water quality [19].

3.1.5. *Predictive analytics*

Predictive analytics is a type of AI that uses machine learning algorithms to analyze data and make predictions about future events or trends. In the context of WRM, predictive analytics can be used to predict water usage patterns during times of drought, water quality trends, and other important metrics [46].

The items explained above are some of the most commonly used AI technologies in the WRM domain. By understanding the capabilities and limitations of each technology, WRM agencies can select the most appropriate AI technologies to meet their specific needs and support sustainable and effective water management practices. Fig. 1 illustrates AI and related tools applied to WRM.

3.2. *The applications of AI in water resource management*

By utilizing AI and big data analytics, WRM agencies can improve their decision-making processes, optimize their water management practices, and ensure a sustainable and equitable supply of water.

AI technologies, such as machine learning algorithms and predictive analytics, can analyze large amounts of data to identify patterns and make predictions accordingly. This information can be used to improve the accuracy of water management processes, such as water allocation and demand forecasting [25].

Furthermore, AI can be used to monitor water quality in real-time (Fig. 2) and alert WRM agencies of any changes in this parameter. This information can be used to make informed decisions about water management practices and to protect water ecosystems [47].

Moreover, AI can be used to optimize water allocation, by analyzing data from water resources, water usage patterns, and other sources. This information can be used to make informed decisions about water management practices and to allocate water resources more efficiently and equitably [49].

AI technologies can also be used to detect leaks and other inefficiencies in water infrastructure. This information can be used to reduce wastewater and to optimize water usage patterns [50].

Additionally, AI can be used to predict water demand based on data from water infrastructure, water usage patterns, and other sources. It helps authorities make informed decisions regarding water management practices and supply water sustainably and equitably [51].

Table 1 summarizes the application of AI in WRM. By leveraging the capabilities of AI and BDA, WRM agencies can make more informed decisions, optimize their water management practices, and ensure a sustainable and equitable supply of water for communities and ecosystems.

4. Innovations in BDA for water resource management

4.1. *Big data analytics in water resource management*

BDA is an important tool for WRM, as it allows WRM agencies to analyze a large number of data and make informed decisions [63]. Some of the innovative ways in which BDA can be applied to WRM include.

4.1.1. *Real-time monitoring of water resources*

BDA can be used to monitor water resources in real-time, and to track changes in water quality, water allocation, and water demand. This information can be used to make informed decisions about water management practices [64].

4.1.2. *Optimizing water allocation*

BDA can be used to analyze water usage patterns and other data sources to optimize water allocation. This can help to allocate water resources more efficiently and equitably [23].

4.1.3. *Improving water demand forecasting*

BDA can be used to predict water demand based on data from water infrastructure, water usage patterns, and other sources. This information can be used to make informed decisions about water management practices and to ensure a sustainable and equitable supply of water [65].

4.1.4. *Detecting wastewater*

BDA can be used to detect leaks and other inefficiencies in water infrastructure. This information can be used to reduce wastewater and to

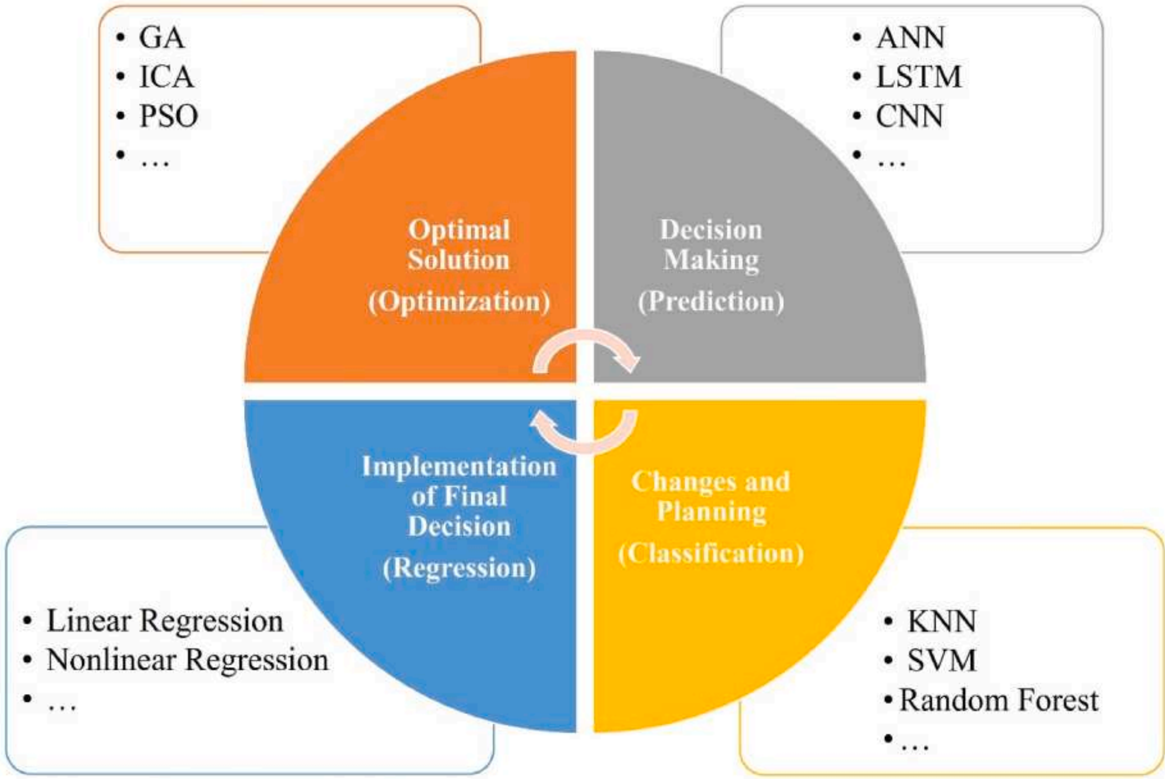

Fig. 1. AI for water resources management.

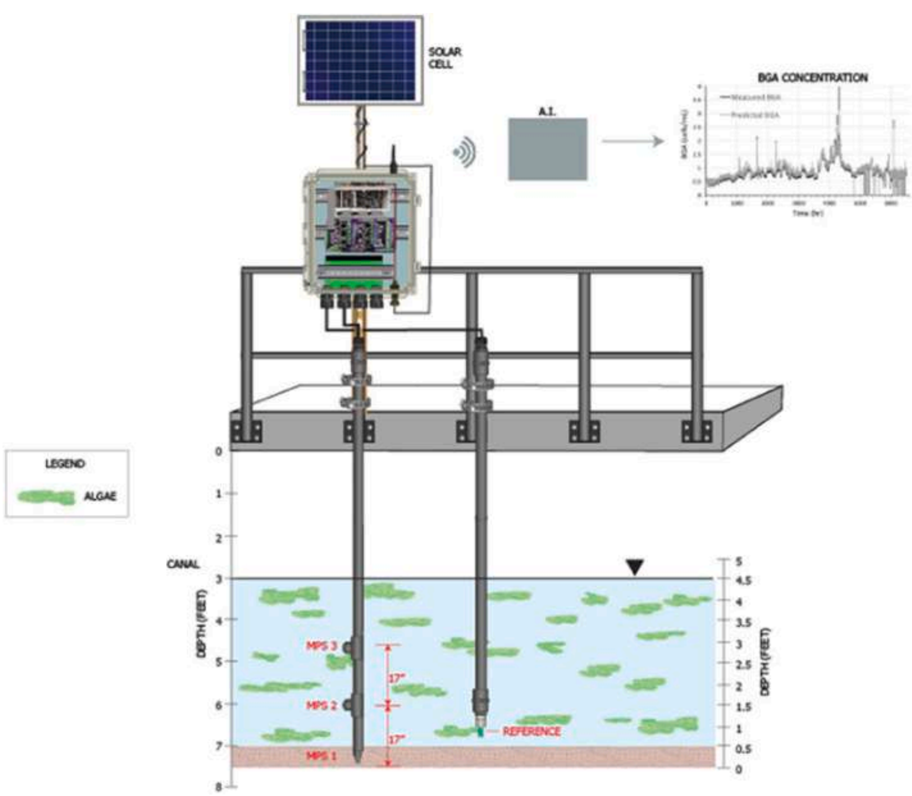

Fig. 2. Real-time monitoring and prediction of water quality (Reproduction with permission from Ref. [48]).

optimize water usage patterns [66].

4.1.5. Enhancing water quality monitoring

BDA can be used to monitor water quality and to identify patterns and make predictions about changes in this parameter. It can help to

Table 1
The application of AI in WRM.

Application	Input	Algorithm	Sample Size	Ref.
Prediction of water quality	pH, Dissolved oxygen, Nitrate, BOD, Conductivity, Fecal coliform, and Total coliform	MLP, DT, SVM, LR, RF, XGBoost, and CATBoost	1679	[52]
Prediction of water quality	pH, AMN, BOD, MRP, DOX, TON, SAL, TRAN, CHL, and TEMP	KNN, SVM, DT, RF, LR, XGB, ExT, and GNB	–	[53]
Dissolved Oxygen prediction	DO	LSTM	236	[54]
Algal bloom prediction	BOD, COD, TSS, and TOC	ANFIS	896	[55]
Prediction of TP, TRP, NH_4–N, NO_3–N	Chlorophyll-a, temperature, pH, DO, EC, flow rate, and turbulence	RF	21657	[56]
Water pollution monitoring	Water images	ANN	1000	[57]
Prediction of water quality	DO, pH, NH_3–N, and CON_{Mn}	RF, DT, and DCF	33612	[27]
Dissolved Oxygen prediction	DO, temperature, Cl, pH, NO_x, and TDS	CCNN	232	[58]
Heavy Metal Assessment	Cr, Cu, Zn, Mn, Cd, Pb, Co, and Ni	PCA	42	[59]
Chlorophyll-a prediction	Chlorophyll-a, temperature, PO_4–P, NO_3–N, NH_3–N, wind speed, and solar radiation	ANN and SVM	357	[26]
TP and TN prediction	TP, TN, DO, temperature, river flow, rainfall, and flow travel time	ANN and SVM	660	[60]
Leakage detection	Not Available	RNN and LSTM	Actual data (59 days)	[61]
Water demand forecast	Maximum Temperature Celsius (°C), Average Temperature Celsius (°C), Humidity Percentage (%), Wind speed Kilometer/hour, and Pressure Millibar Rainfall	Linear Regression Model, Decision Tree Model, SVM, KNN, Random Forest, XGBoost, ARIMA, ANN, and LSTM	Data were gathered from January 2020 to October 2021	[62]

make informed decisions about water management practices and to protect water ecosystems [67].

The use of BDA in WRM can help WRM agencies to make more informed decisions, optimize their water management practices, and ensure a sustainable and equitable supply of water for communities and ecosystems [68]. These application are summarized in Table 2.

4.2. Different data sources that can be leveraged in water resource management

In water resource management, there are various data sources that can be leveraged to support decision-making and optimize water management practices. Some of the most common data sources include:

4.2.1. Remote sensing

Remote sensing technologies, such as satellites and unmanned aerial vehicles, can be used to gather information about water resources and water ecosystems. This information can be used to monitor changes in water quality, water allocation, and water demand and to make informed decisions about water management practices [32].

Table 2
BDA in water resource management.

Application	Input Data	Algorithm	Sample Size	Ref.
Real-time monitoring of water resources	Temperature, PH, Turbidity, DO, Conductivity, BOD, NI, FC, TC, and WQI	Refined stochastic gradient descent (SGD)	1600	[64]
Optimizing water allocation	Temperature, Pressure, Water Quality Air Quality, and Humidity	Resource provisioning methods in cloud-based IoT environments	N/A	[23]
Improving water demand forecasting	Occupation Rate (%) Av BARs 1 week Av BARs 2 week Av BARs 3 week Av BARs 4 week # rooms (nrooms) # meeting rooms (nmr) # restaurant seats (nrs) Km from city center (dist) Km from airport (dista)	Smart method based on Seasonal Auto-Regressive Moving-Average (SARIMA)	274 Days	[65]
Detecting wastewater	DO, COD-Mn, NH4–N, and Overall water quality	Water Quality Identification Index (WQII)	68330	[66, 69]
Enhancing water quality monitoring	Seokseong WTP data (Korea)	Artificial Neural Network (ANN) and Deep Neural Network (DNN)	42662	[67]

4.2.2. IoT devices

The increasing availability of IoT devices, such as sensors and smart meters, can aid in gathering information about water usage patterns and water infrastructure. This information can be used to monitor water usage patterns, detect leaks and inefficiencies, and optimize water allocation (Fig. 3) [70].

4.2.3. Social media

Social media platforms, such as Twitter and Facebook, can be used to gather information about water usage patterns and water quality. For example, communities can use social media to report water outages, leaks, and other issues, which can then be used by WRM agencies to respond more effectively [71].

4.2.4. Hydrological models

These models can be used to simulate the flow and quality of water in water systems. These models can be informed by data from remote sensing, IoT devices, and other sources to make more accurate predictions about water usage patterns and water quality [72,73].

By leveraging these various data sources, WRM agencies could make more informed decisions, respond more effectively to water-related issues, and ensure a sustainable and equitable supply of water for communities and ecosystems.

5. The applications of AI and BDA in real-scale water resource management

5.1. Integration of AI and BDA into water resource management

The integration of AI and BDA into water resource management has

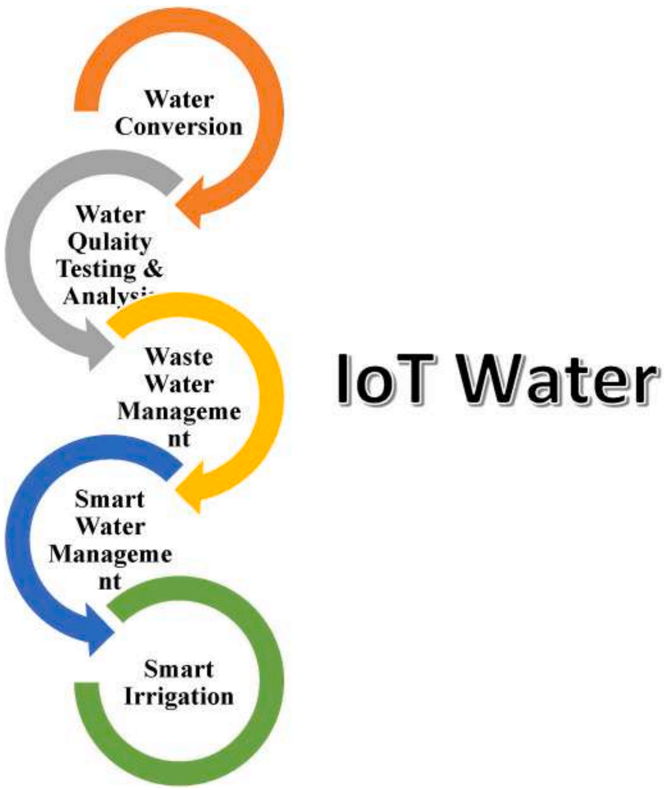

Fig. 3. IoT for water management systems.

been gaining significant attention in recent years. This is due to the challenges traditional water resource management practices are faced with, including population growth, climate change, and increasing water demand, which highlight the need for new and innovative approaches [17]. AI and BDA can provide a valuable tool to support sustainable and effective water management practices and protect water ecosystems [74,75]. Fig. 4 illustrates an example of how AI can be used to manage real-scale water resources. In fact, this figure shows how AI can help manage water resources toward environmental sustainability.

One of the key applications of AI in WRM is the monitoring of water quality. AI algorithms can be used to analyze data from various sources, including remote sensing, IoT devices, and laboratory tests, to monitor water quality in real-time and detect any changes or anomalies in water quality [77]. This information can then be used to make informed decisions about water treatment and distribution and to respond to changes in water quality more quickly and effectively.

Another important application of AI in this domain is water allocation. AI algorithms can optimize water allocation, ensuring the equitable and sustainable distribution of water. This can be done by analyzing data from IoT devices [78,79], remote sensing, and other sources to make more informed decisions about water usage patterns and water demand. For example, AI algorithms can be used to identify areas where water usage is higher than average or water quality is lower than expected; they can make recommendations to address these issues [80].

Water demand forecasting is another key application of AI in WRM. AI algorithms can be used to forecast water demand and predict changes in water usage patterns. This information can be used to make informed decisions about water allocation and to ensure that there is enough water available to meet the communities' and ecosystems' requirements [81]. By using AI and BDA to forecast water demand, WRM agencies can make more informed decisions about water allocation and respond more quickly and effectively to changes in water usage patterns [28].

Finally, AI and BDA can also be used to monitor and optimize water infrastructure, such as pipelines, reservoirs, and treatment plants. For example, AI algorithms can be used to detect leaks and inefficiencies in pipelines and to make water distribution and treatment processes optimized. This can help to reduce water waste, improve water quality, and ensure that water is used more efficiently and sustainably [64].

In summary, the integration of AI and BDA into water resource management provides a valuable tool to support sustainable and effective water management practices. By incorporating these technologies, water resource management agencies can make more informed decisions, respond more quickly and effectively to water-related issues, and ensure a sustainable and equitable supply of water for communities and ecosystems [82].

5.2. The benefits and limitations

The utilization of AI and BDA in WRM brings a range of benefits and limitations, which must be considered when seeking for effectiveness and sustainability in water management practices. One of the key benefits of these innovations is that they allow for more efficient and accurate monitoring of water resources [36]. This includes the ability to monitor water quality, allocate water resources effectively, and forecast water demand [22,83,84]. By leveraging various data sources such as remote sensing, IoT devices, and social media, AI and BDA can provide real-time insights into WRM, which have previously been impossible [18].

However, despite these benefits, there are also some limitations to be considered, too. For example, there are concerns about the accuracy of data and how to handle large amounts of data. Additionally, there may be challenges in integrating AI and BDA systems into existing water resource management practices, which can lead to resistance from stakeholders who are accustomed to traditional methods [85]. Furthermore, there may be concerns about the potential for AI and BDA systems to perpetuate existing biases and discrimination in WRM practices, which is particularly important given the critical nature of water as a resource [49].

It is therefore important to carefully consider the benefits and limitations of these innovations in the WRM context to ensure that they are deployed in a manner that supports sustainability and effectiveness of water management practices. This can be achieved through the development of guidelines for the use of AI and BDA in the WRM domain and the involvement of relevant stakeholders in the design and implementation of these systems [86].

6. Conclusions

The intersection of AI and BDA has emerged as a beacon of innovation, illuminating a path to more effective, adaptive, and sustainable water management strategies. This article discussed the most recent and prospective applications of these technologies, highlighting their transformative potential in addressing the multifaceted complexities of water resources. AI and BDA have unveiled a new dimension of data-driven decision making, from the unprecedented accuracy of flood forecasting to the real-time monitoring of water quality. The ability to assimilate vast and disparate datasets from a variety of sources, coupled with the computational prowess of AI algorithms, has allowed water resource managers to transcend traditional boundaries and delve deeper into the complexities of water systems.

This paper demonstrated the extensive and multifaceted applications of AI and BDA in forecasting the availability of water, optimizing allocation, and improving infrastructure maintenance. In addition, these technologies fill monitoring voids, empower communities, and provide previously unavailable information to decision-makers. This investigation into the most recent innovative avenues highlighted the significance of collaboration between various stakeholders. Researchers, policymakers, engineers, and communities must leverage the potential of these technologies while maintaining vigilance regarding ethical concerns, data privacy, and equitable access to benefits.

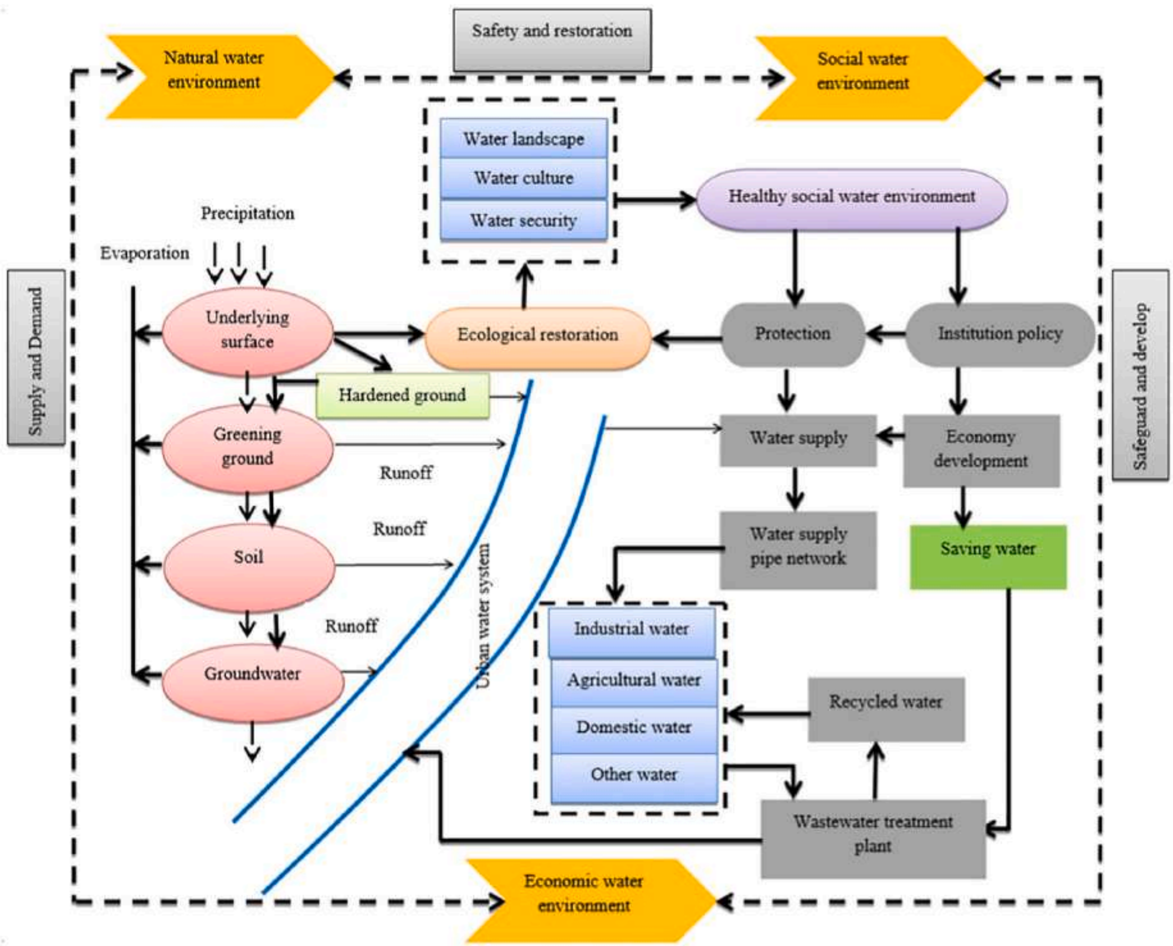

Fig. 4. A schematic of application of the AI technique for WRM in real-scale (Reproduction with permission from Ref. [76]).

On the other hand, the process of incorporating AI and BDA into WRM is limited with different obstacles. Because of technical complexities, data constraints, and the requirement for interdisciplinary expertise, it is essential that a concerted effort be made by professionals. Nevertheless, the benefits are substantial: a resilient water future that navigates the uncertainties of climate change, sustains flourishing ecosystems, and ensures equitable access to this precious resource.

In conclusion, the focus on these innovative avenues represents a paradigm shift in our approach to WRM. With AI and BDA as our guides, we embark on a transformational voyage that redefines our understanding, strategies, and actions regarding the protection of one of the most essential resources for life on the Earth. We are poised to leave a legacy of sustainable water management for future generations as we pave this new path.

7. Future directions

The integration of AI and BDA offers numerous opportunities to further improve WRM as a result of the continuous development of technology. As these technologies continue to develop, their potential impacts on addressing complicated WRM challenges grow. This section outlines a number of promising future directions for applying AI and BDA to the WRM domain. Future applications of AI and BDA in WRM will likely make use of spatial and temporal data with a higher resolution. With the use of remote sensing technologies, such as satellites and drones, it is possible to collect comprehensive data on water availability, land use changes, and ecosystem health. By combining these datasets with cutting-edge AI algorithms, decision-makers can obtain more precise insights, allowing for more targeted and timely interventions.

In the future of WRM, the proliferation of IoT devices capable of accumulating and transmitting real-time data will play a crucial role. These devices, which are imbedded in water infrastructure, ecosystems, and urban areas, can continuously provide data on water quality, discharge rates, and weather conditions, among other parameters. These streaming data can be processed by AI algorithms to provide immediate insights, allowing for expeditious responses to shifting conditions and facilitating proactive management.

AI and BDA will continue to refine models for predicting extreme events like flooding, droughts, and water quality crises. By incorporating sophisticated techniques of machine learning and enhanced data inputs, these models are able to provide more accurate and reliable predictions. This will allow authorities to take preventative measures, lessening the impact on water systems and communities. Future applications will likely emphasize the integration of AI and BDA into decision support systems. These systems will provide decision-makers with an intuitive interface that synthesizes complex data and model outputs into actionable recommendations. Such platforms will increase the availability of data-driven insights and allow even non-specialists to make informed decisions in WRM.

Future WRM will emphasize collaborative approaches incorporating multiple sectors and communities. AI and BDA can facilitate participatory decision-making by providing interactive data visualization and outcome modeling tools. These tools allow stakeholders to investigate different scenarios, comprehend trade-offs, and develop adaptive strategies that balance diverse interests collectively. WRM models will progressively incorporate socioeconomic data derived from AI and BDA. These technologies can provide a comprehensive understanding of water demand, utilization patterns, and community impacts by analyzing economic trends, demographic shifts, and behavioral patterns. This integrated approach will foster management strategies that are more inclusive and equitable. Future research could concentrate on techniques to improve the interpretability of AI models. As the complexity of AI algorithms increases, it becomes essential to ensure that decisions are transparent and intelligible. AI advancements that are explicable will allow decision-makers to trust and perceive the reasoning behind AI-driven recommendations.

Efforts to adapt AI and BDA for tiny and limited-resource regions are acquiring momentum. Future directions will include the development of models that require fewer data inputs and computational resources, allowing these technologies to be effectively applied in regions with limited infrastructure. Concerns regarding data privacy, algorithmic biases, and equitable access to benefits must be addressed as AI, and BDA becomes increasingly integrated into WRM. Future directions will include the development of ethical frameworks and guidelines to ensure the application of these technologies in a responsible and equitable manner.

In summary, the sustained integration of AI and BDA bears immense promise for the future of WRM. These technologies have the potential to transform the understanding, management, and conservation of water resources. As researchers, practitioners, and policymakers collaborate to investigate these future directions, the result will be water systems that are more resilient, sustainable, and adaptive to the benefit of both current and future generations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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