Fronteiras: Journal of Social, Technological and Environmental Science
http://periodicos.unievangelica.edu.br/fronteiras/
ISSN 2238-8869

Article

Technologies Used in the Quantitative and Qualitative Monitoring of Water: The Use of Artificial Intelligence in Predicting Extreme Events

Samuel Ribeiro dos Santos[1], **Samylla Oliveira Almeida**[2]

[1] Graduado em Tecnologia em Gestão de Turismo. Instituto Federal de Educação, Ciência e Tecnologia do Sudeste de Minas Gerais. ORCID: 0009-0009-4651-2777. Email: guiasamuelsantos@icloud.com
[2] Doutora em Engenharia Civil (Recursos Hídricos) - Área de Concentração: Saneamento Ambiental. Docente Efetiva no Instituto Federal de Educação, Ciência e Tecnologia do Sudeste de Minas Gerais. ORCID: 0000-0002-6665-8257. Email: antonia.almeida@ifsudestemg.edu.br

Resumo
A urgência da escassez hídrica, intensificada por eventos hidrológicos críticos, e a ineficácia do Monitoramento da Qualidade da Água (MQA) tradicional, dispendioso, lento e sem dados imediatos demanda o uso de novas tecnologias. Diante disso, buscou-se responder: quais os avanços e limitações na utilização da Inteligência Artificial (IA) para o Monitoramento de Recursos Hídricos (MRH), em comparação com os métodos tradicionais? Metodologicamente, a presente pesquisa consistiu em análise bibliográfica, qualitativa, exploratória e descritiva. Foram selecionados 21 artigos (2020-2024) das bases *Google Scholar*, *SciELO* e *Web of Science*, complementada por análise cienciométrica. A discussão de resultados indicou que a integração da IA com a Internet das Coisas ou *Internet of Things* (*IoT*) impulsiona a transformação digital, permitindo automação, monitoramento contínuo e respostas rápidas, superando as falhas do MQA tradicional. Contudo, as limitações incluem: complexidade de modelagens, dados de baixa qualidade, altos custos e dificuldade para abordar aspectos humanos e sociotécnicos, como equidade. Conclui-se que IA e *IoT* são avanços cruciais para a gestão sustentável, mas é fundamental preencher lacunas de pesquisa sobre os impactos ambientais e integrar o fator humano nos sistemas hídricos.
Palavras-chave: Eventos hidrológicos críticos; Monitoramento quali-quantitativo; Automação; Gestão de recursos hídricos.

Abstract
The urgency of water scarcity, intensified by critical hydrological events, together with the ineffectiveness of traditional Water Quality Monitoring (WQM), which is costly, time-consuming, and lacks real-time data, demands the adoption of new technologies. In this context, this study sought to address the following question: what are the advances and limitations in the use of Artificial Intelligence (AI) for Water Resources Monitoring (WRS) compared to traditional methods? Methodologically, the present research consisted of a qualitative, exploratory, and descriptive bibliographic analysis. A total of 21 articles published between 2020 and 2024 were selected from the Google Scholar, SciELO, and Web of Science databases and complemented by a scientometric analysis. The discussion of the results indicated that the integration of AI with the Internet of Things (IoT) drives digital transformation, enabling automation, continuous monitoring, and rapid responses, thereby overcoming the shortcomings of traditional WQM. However, the limitations include model complexity, low data quality, high costs, and difficulties in addressing human and sociotechnical aspects, such as equity. It is concluded that AI and IoT represent crucial advances for sustainable management; nevertheless, addressing research gaps related to environmental impacts and integrating the human factor into water systems remain essential.
Keywords: Critical hydrological events; Qualitative and quantitative monitoring; Automation; Water resources management.

Submissão: 20/02/2026 Aceite: 03/09/2026 Publicação: 14/11/2026

v.15, n.3, 2026 • p. 1-17. • DOI http://dx.doi.org/10.21664/2238-8869.2026v15i3.8616

© 2021 by the authors. Esta revista oferece acesso livre imediato ao seu conteúdo, seguindo o princípio de que disponibilizar gratuitamente o conhecimento científico ao público proporciona maior democratização mundial do conhecimento. Este manuscrito é distribuído nos termos da licença Creative Commons – Atribuição - NãoComercial 4.0 Internacional (https://creativecommons.org/licenses/by-nc/4.0/legalcode), que permite reproduzir e compartilhar o material licenciado, no todo ou em parte, somente para fim não comercial; e produzir, reproduzir, e compartilhar material adaptado somente para fim não comercial.

Introduction

Water scarcity is a persistent problem, intensified by the imbalance between supply and demand and by the increase in critical hydrological events, such as floods and droughts, frequently associated with climate variations, which generate negative impacts on life and the economy, making the adoption of new technologies for the sustainable management of water resources urgent (Yang & Liu 2020).

In this context, the importance of monitoring combined with new technologies stands out, since traditional Water Quality Monitoring (WQM), based on laboratory analyses, although accurate, is costly, slow, labor-intensive, and lacks real-time data (Zhuiykov 2012; Murphy et al. 2015; Gholizadeh et al. 2016; Yaroshenko et al. 2020). Therefore, the water sector has been moving toward Industry 4.0, adopting emerging technologies such as Artificial Intelligence (AI), which are essential to the process of "digital transformation of water" (Ngila et al. 2020; Matheri et al. 2020).

Seeking to broaden the discussion on the use of these technologies in water resources actions, four aspects were considered: the need to comply with legal recommendations for the qualitative and quantitative monitoring of water resources; the relevance of the topic given the emergence of technologies capable of assisting these processes, already applied in other industrial sectors; the imminence of climate change, which affects various resources and socioeconomic sectors; and the fact that this is a relatively new topic, still with a limited number of peer-reviewed studies published.

Finally, this review fills a gap regarding the use of AI and other technologies in water monitoring, describing technological, operational, and sociotechnical advances and limitations. Thus, to answer the question, "what are the advances and limitations in the use of Artificial Intelligence (AI) in Water Resources Monitoring (WRM) compared to traditional methods?", a bibliographic study was conducted, of a basic nature, with a qualitative approach and exploratory and descriptive objectives. Therefore, the text was organized into: theoretical framework, methodology, discussion of results, and conclusion.

Theoretical Framework

Currently, water scarcity persists due to the imbalance between supply and demand, aggravated by disasters such as floods and droughts, making water resources management difficult and indicating that many developing countries may face severe scarcity by 2025 (Yang & Liu 2020; Boretti & Rosa 2019; Du Plessis & Du Plessis 2019; Mancosu et al. 2015).

The increase in catastrophic events, such as floods and droughts, compromises the achievement of the Sustainable Development Goals (SDGs) (Nações Unidas Brasil 2024), by causing loss of life, material damage, destruction of crops, and outbreaks of waterborne diseases (Yang & Liu 2020). In this context, climate variations associated with global warming intensify extreme precipitation and temperature events, increasing hydrological variability and the frequency of droughts and floods (Bakker 2012; Clark 2014).

Critical Hydrological Events: Floods and Droughts

The natural disaster classification system comprises six groups: biological, geophysical, meteorological, hydrological, climatological, and extraterrestrial (Below et al. 2009), with floods classified within the hydrological group (fluvial, pluvial, and coastal) and droughts within the climatological group (Yang & Liu 2020).

Pluvial flooding results from rainfall runoff and the formation of pools before the water reaches watercourses or drainage systems, or when these systems are saturated (Falconer et al. 2009). According to Yang and Liu (2020), it occurs in rural areas when precipitation exceeds soil infiltration and, in urban areas, when it exceeds the capacity of stormwater drainage systems. Its recurrence intensifies impacts and threats to life and is aggravated by climate change (Hurford et al. 2011; Kaźmierczak & Cavan 2011).

Among fluvial floods, transboundary flooding, the most common type, occurs when rivers overflow, while flash flooding is characterized by an intense and rapid flow occurring within up to six hours or by the failure of dams or dikes (Yang & Liu 2020). These events, when associated with debris, are highly dangerous and destructive due to the force of the water and the shorter warning and response times compared with conventional floods (Archer & Fowler 2018).

Coastal floods are caused by large waves, storm surges, high tides, and anomalies in mean sea level (Yang & Liu 2020), and may also be influenced by precipitation and river flow in deltas and estuaries (Wolf 2008). In densely populated regions affected by tropical cyclones, rates of sea-level rise approach or exceed the global average (Woodruff et al. 2013). Although generally associated with losses, these floods can also perform

essential ecosystem functions, such as aquifer recharge, increased biodiversity, and connectivity of aquatic habitats (Yang & Liu 2020).

Droughts, which belong to the climatological group, have varying definitions depending on hydrometeorological conditions, geographic location, and water demands (Mishra & Singh 2010). Organizations such as the World Meteorological Organization (WMO) and the United Nations Secretariat General define them as conditions of precipitation deficiency (WMO 1986; United Nations Secretariat General 1994), and they are classified into four categories: meteorological drought, hydrological drought, agricultural drought, and socioeconomic drought (American Meteorological Society 2004; Mishra & Singh 2010).

Meteorological drought is characterized by precipitation deficits in a region over a given period, occurring when rainfall levels remain below average and being strongly associated with sea surface temperature and thermal anomalies (Gibbs 1975; Yang & Liu 2020). Hydrological drought, on the other hand, refers to periods of scarcity of surface and groundwater, such as rivers, lakes, and aquifers, compromising the supply required for established uses, such as human water supply and the maintenance of aquatic ecosystems (Mishra & Singh 2010; Wali et al. 2024).

According to Sheffield and Wood (2011), hydrological droughts can cover large areas and last from months to years, differing from meteorological droughts due to the characteristics of the climate and river basins (Hasan et al. 2019), and are primarily analyzed using streamflow data rather than precipitation data (Van Loon 2015; Hasan et al. 2019). Agricultural drought, on the other hand, refers to reduced soil moisture and the consequent loss of productivity, without direct reference to surface water resources (Mishra & Singh 2010; Allah et al. 2017), generally preceded by persistent meteorological droughts that evolve into agricultural, hydrological, and socioeconomic droughts (Schubert et al. 2016).

Finally, socioeconomic drought occurs when the demand for economic goods exceeds supply as a result of climate-related water scarcity (Mishra & Singh 2010). Thus, meteorological, hydrological, and agricultural droughts measure drought as a physical phenomenon (Yang & Liu 2020), whereas socioeconomic drought is the type that has a direct impact on human production and everyday life (Guo et al. 2019).

Various impacts result from poor water supply management and critical hydrological events, including risks to life, economic damage, and threats to water security associated with droughts and floods (Kesarwani et al. 2023; Yang & Liu 2020; Guo et al. 2019). Addressing these impacts requires coordination among all actors involved in water management and the adoption of new digital technologies to handle large volumes of data, integrate information, combine big data and theoretical modeling, and ensure sensor data quality (Matheri et al. 2022). In this regard, the following section presents a theoretical overview of water resources monitoring models, focused on the qualitative and quantitative monitoring of water, the prevention of scarcity, and the mitigation of critical hydrological events.

A Brief Overview of Conventional Monitoring Models

Factors such as emerging contaminants, climate change, population growth, rural-to-urban migration, variations in pollutant discharge, human activities, and the lack of adequate sanitation, especially in developing countries, cause rapid deterioration in the quality of surface and groundwater (Ahmed et al. 2019b; Jia et al. 2021; Aakash et al. 2024), and require monitoring actions for proper management.

In this context, Water Quality (WQ) refers to the biological, chemical, and physical properties that determine its suitability for specific uses, being mainly influenced by parameters suspended or dissolved in water (Ahmed et al. 2019a; Pulé et al. 2017; Department of Water Affairs and Forestry 1996).

Traditionally based on laboratory analyses, WQM involves the collection and preservation of water samples from specific sources, which are subsequently sent to accredited laboratories, supporting monitoring assessment and the recommendation of future actions (Paepae et al. 2021). WQM is based on the periodic detection of parameters at defined locations to provide data and identify current conditions or trends (Adu-Manu et al. 2017). The interpretation and communication of results constitute critical stages of this process, which generally follows a logical sequence of monitoring, assessment, and management (Chapman 1996; Paepae et al. 2021).

WQM is governed by national guidelines in most countries and is traditionally based on laboratory approaches (Paepae et al. 2021). Although still predominant in many developing countries, the conventional method presents limitations, such as high costs for laboratory implementation and maintenance, the need for specialized equipment and personnel, the possibility of sampling and calibration errors, the absence of real-time data, in addition to being labor-intensive and time-consuming (Gholizadeh et al. 2016; Yaroshenko et al. 2020).

Furthermore, conventional treatments have proven to be ineffective against emerging contaminants, such as pharmaceuticals, and adapting processes and infrastructure increases costs (Paepae et al. 2021). However, their precision, accuracy, and compliance with standardized techniques for regulatory and legal purposes maintain the relevance of this traditional approach (Zhuiykov 2012; Murphy et al. 2015).

The first advancement in physical sensors for WQM occurred around 1930, with the glass pH electrode coupled to a pH meter (Yaroshenko et al. 2020). Subsequently, research expanded the development of sensors for parameters such as dissolved oxygen, turbidity, temperature, chlorophyll-a, electrical conductivity, ammonia nitrogen, and salinity, resulting in mature and low-cost devices (Chen et al. 2020).

With the advancement of portable sensors, computing, and communication, Wireless Sensor Networks (WSNs) began to be adopted in WQM, performing parameter readings, transmitting data to a central station for analysis, and forwarding the results to water authorities (Ahmed et al. 2019a; Jan et al. 2021; Paepae et al. 2021). Although WSNs have mitigated limitations of previous systems, they still present constraints, such as high energy consumption, vulnerability to cyberattacks, high installation and maintenance costs, and data storage problems (Paepae et al. 2021; Pulé et al. 2017; Jan et al. 2021).

A Perspective on the Use of Artificial Intelligence and Other Technologies in the Context of Water Scarcity and Water Quality Monitoring

Agricultural Sector

Usual monitoring approaches have led to a scenario in which human ambitions exceed the limits of the planet (Silva 2022). In this context, the risks of water scarcity, resulting from increased demand and the reduction of water supply sources due to environmental impacts, pollution, and climate change, intensify the search for new technologies that ensure access to water in a robust, efficient, and reliable manner (Elimelech & Phillip 2011).

According to the Food and Agriculture Organization (FAO) (2021), agriculture is estimated to consume approximately 70% of the world's freshwater. In this context, increasing water-use efficiency in the agricultural sector is fundamental for the sustainable management of water resources (Sindhu et al. 2024; Tarate et al. 2024). In this regard, El Bilali and Taleb (2024) highlight the growing use of Machine Learning (ML) algorithms and IoT to address complex irrigation management challenges.

According to Mgendi (2024), AI-based irrigation systems autonomously regulate water use based on soil moisture, weather forecasts, and crop demands, ensuring efficiency and reducing waste. Furthermore, AI models make it possible to predict water requirements and optimize irrigation planning, increasing water-use efficiency and crop yields (Kamarbekov & Baimaganbetov 2024).

AI applications in the agricultural sector also encompass broader practices, such as decision-support tools that combine Dominance-based Rough Set Approach (DRSA) and ML approaches for crop selection based on multiple criteria, although their implementation is still limited by the scarcity of real-time data on parameters such as soil moisture and evapotranspiration (Assimakopoulos 2024; Tarate et al. 2024).

In the livestock sector, aquaculture has sought to optimize WQ, fish health monitoring, and overall management through IoT, AI, and ML technologies; however, despite the advances, there remains a research gap regarding the environmental impacts of deploying IoT devices in aquatic ecosystems, particularly concerning chemical pollution and radiation exposure (Senoo et al. 2024).

Human Water Supply and Sanitation Systems

Digital transformation, driven by big data, data analysis, AI, and digital tools such as sensors, digital twins, data mining and pipelines, IoT, water monitoring, and nanotechnology, expands water management capabilities (Garrido-Baserba et al. 2020; Poch et al. 2020). This process has generated a large volume of data from sensors and operational sampling, driving computational development and revolutionizing various economic sectors (Van Loosdrecht & Brdjanovic 2014).

According to Matheri et al. (2022), it is essential to ensure a reliable and safe water supply combined with proper management in a water sector transitioning to Industry 4.0, which involves water resource recovery

facilities and the integration of energy, water, soil, climate, food, heat, chemicals, and data-intensive information sources (Garrido-Baserba et al. 2020).

The adoption of emerging digital systems in the Fourth Industrial Revolution (4IR), known as the digital transformation of water, reduces the gap between current operations and cutting-edge technologies, such as online sensors, wireless communication, IoT, big data, ML, and other AI tools, as well as modeling, simulation, advanced algorithms, and digital twins associated with virtual reality, becoming essential for the description, control, prediction, and prognosis of Wastewater Treatment Plants (WWTPs) (Ngila et al. 2020; Matheri et al. 2020).

In wastewater treatment (WWT), AI acts as a powerful tool by simplifying and accelerating complex procedures (Alharbi 2024). However, despite the interaction between big data and AI in the analysis, organization, and extraction of data-based information for WWT operation and control (Blumensaat et al. 2019; Garrido-Baserba et al. 2020), optimization through online models is still little applied in water and wastewater treatment due to the complexity of modeling, the biological behavior of processes, the absence of visualization techniques, and the low quality of industrial measurements (Matheri et al. 2022).

According to Poch et al. (2020), due to the complexity of technologies applied to water management, an interdisciplinary and sociotechnical approach is required that integrates water engineering systems and social aspects, such as equity, legal issues, and data privacy. This requires sustainable circularity, intelligent data-driven operations, and control of the Wastewater Treatment Plant (WWTP) aligned with the SDGs and the Industry 4.0 framework (Matheri et al. 2022).

According to Verde Neto and Souza Filho (2022), throughout history, WWT has faced technical and political challenges, as exemplified in Australia, where droughts, high electricity costs, and dependence on costly sources, such as desalination, intensify concerns about sustainability (Sorbello & Marck 2014).

Therefore, addressing the water-related problem requires measures such as the decentralization of rainwater harvesting (Partzsch 2009), participatory governance (Bakker & Cook 2011), sustainable business models, and the promotion of a "green market" (Boons et al. 2013), reinforcing the view that the interaction between human habits and technology directly influences water systems (Matheri et al. 2022).

The water sector faces new challenges for the sustainable management of urban systems due to external factors such as climate change, droughts, and population growth; furthermore, the low priority attributed to water services in government actions is evident in the challenges of maintaining reliable and safe service in the face of aging infrastructure (Joseph et al. 2022), and population and urban growth (Velayudhan et al. 2022). Thus, Cenci et al. (2023) point out that, in the face of intense climate changes caused by human actions, such as pollution, water scarcity, deforestation, and forest fires, smart cities emerge as an appropriate model for addressing the main problems of society.

Concerns about water security can be grouped into four categories: direct risks to drinking water supply systems; water resource scarcity and its effects on economic growth; threats to aquatic ecosystems resulting from pollution, excessive water use, and biodiversity loss; and impacts of climate change, which increase hydrological variability and the frequency of droughts and floods (Bakker 2012; Clark 2014).

In this context of deficient infrastructure and smart cities, Integrated Water Networks or Smart Water Networks (SWNs) are fundamental for optimizing network management, reducing failures and losses, ensuring operational sustainability, and incorporating digital technologies for automation and decision-making, improving service quality and reducing risks in the face of increasing demands (Bush & Uber 1998; Marney & Sharma 2012; Morosini et al. 2017). Parameters for the development of an SWN include system elements, such as pipelines, reservoirs, tanks, and pumps, as well as water quantity and quality parameters, used to monitor supply and ensure potability standards (Joseph et al. 2022).

Various AI approaches, such as Neuro-Fuzzy Systems (NFS) and Support Vector Machines (SVM), are employed to predict pipeline failure and assess the reliability and performance of SWN systems (Kutyłowska 2015). Bubtiena et al. (2011) proposed Artificial Neural Network (ANN) models for pipeline failures, making it possible to define rehabilitation strategies, proactive maintenance, and prioritization of actions. Complementarily, Asnaashari et al. (2013) indicate that the increase in failures results from poor maintenance and aging systems, with ANN modeling being effective in defining repair and replacement priorities.

According to Velayudhan et al. (2022), the water sector can no longer remain isolated from the technological transformations observed in other infrastructure sectors; the growth of IoT is evidenced by data indicating 21.7 billion connected devices worldwide, of which 11.7 billion (54%) are IoT device connections. Furthermore, it is projected that by 2025 there will be more than 30 billion IoT connections, corresponding to an average of four devices per person (Lueth 2019; Manyika 2015).

Some of the main applications of IoT-enabled monitoring systems include pipeline inspection (such as corrosion and cracks), maintenance forecasting, real-time analysis of sensor data to identify leaks, and the use of software that assists utilities and consumers in tracking water consumption, contributing to more efficient water management (Velayudhan et al. 2022).

The use of IoT technologies can be integrated with AI (Govinda & Saravanaguru 2016; Hammi et al. 2017), promoting the progressive transformation of monitoring, control, and automation of Water Distribution Networks (WDNs) (Shah & Yaqoob 2016), with a focus on improving the use of smart sensor data (Plageras et al. 2018; Teng et al. 2019), management and governance of internal water collection, storage, and distribution functions (Gaffoor 2017; Narendran et al. 2017; Robles et al. 2015), detection and reduction of leaks and costs (Maamar et al. 2019), increasing business effectiveness through process automation (Hamdy et al. 2003; Manavalan & Jayakrishna 2019), and improving WQ (Almetwally et al. 2020).

According to Velayudhan et al. (2022), one of the main challenges of WDNs is providing rapid information to utilities and, in this regard, integration with IoT increases the potential of AI technologies to address urgent challenges in these networks. In the context of WDNs, especially regarding the use of technologies, the Water-Energy Nexus (WEN) should be broadly considered. According to Huang et al. (2023), the search for sustainable solutions to water scarcity, the energy crisis, renewable energy production, and the protection of humans and ecosystems is increasingly relevant to the future of the WEN, which refers to the interdependence between water and energy in production, treatment, distribution, and/or recycling processes, at different scales, from community to global (Dai et al. 2018; Machell 2015; Pan et al. 2018; Vakilifard et al. 2018).

Consistent with the arguments of Matheri et al. (2022) and Silva (2022) regarding the human-technology-systems interrelationship, Huang et al. (2023) state that, as the demand for water resources grows to meet water-energy interdependence, a comprehensive analysis of infrastructure and human dimensions becomes fundamental to ensure efficient and sustainable water supply and management within the Water-Energy-Infrastructure-Human Nexus (WEIHN); however, traditional water supply and treatment systems within the WEIHN remain predominantly centralized, encompassing collection, treatment, and energy generation.

Managing these systems from a perspective that integrates infrastructure and human involvement can generate relevant information on challenges and opportunities in the development of WDNs, including the need for reliable and resilient infrastructure and the engagement of stakeholders and communities for the sustainable use of water and energy (Huang et al. 2023). However, capturing data on human behavior, both qualitatively and quantitatively, still represents a significant challenge, highlighting the need for methodological advances within the WEIHN (Bethke et al. 2021).

According to Huang et al. (2023), in the search for solutions to the challenges of Community Water Supply Systems (CWSS), advances have occurred in the development of innovative technologies and strategies aimed at reducing energy consumption and increasing treatment efficiency. The decentralized integrated energy and hydraulic network or Water-Energy-Infrastructure-Human-Nexus (WEIHN) emerges as an alternative approach to increase energy efficiency in CWSS through integrated watershed management strategies for freshwater management (Huang et al. 2023).

However, the balance between energy efficiency and the removal of contaminants — such as heavy metals (Chen et al. 2020), microplastics (Iyare et al. 2020), and perfluoroalkyl substances (PFAS) (Dixit et al. 2019) — remains challenging due to technological limitations and knowledge gaps, especially regarding the systemic context and scalability of new membrane materials with lower energy consumption (McCutcheon & Mauter 2023).

In a decentralized WEIHN, the Decentralized Water Supply System (DWSS) integrates advanced small-scale treatment technologies, such as electrochemical systems with Granular Activated Carbon (GAC) (García et al. 2018) and constructed wetlands (Lakho et al. 2021), meeting WQ requirements with lower energy consumption compared to the centralized WEIHN. In areas with sparse populations or fluctuating demands, the economic viability of the DWSS may even exceed that of the Centralized Water Supply System (CWSS) (Rabaey et al. 2020).

Methodology

This is a bibliographic study of a basic nature and qualitative character, with exploratory and descriptive objectives. The search for bibliography (articles) was conducted, respectively, in the Google Scholar, SciELO, and Web of Science databases using both the Portuguese keywords[1] "monitoring technologies," "water resources," "artificial intelligence," "water scarcity," and "quality," and the strings "monitoring technologies," "water resources," "artificial intelligence," "water scarcity," and "quality." In addition, inclusion and exclusion

criteria were adopted, such as a temporal range (2020–2024), open access, peer review, and the removal of monographs, publications in conference proceedings (abstracts, expanded abstracts, articles, and reviews), dissertations, and theses.

Thus, a total of 43 studies were obtained, whose selection, carried out jointly by the authors, occurred through the reading of their respective titles, abstracts, objectives, and results. From this screening, 21 studies that showed greater adherence to the subject of the work were selected. To avoid any discrepancies regarding the number of studies found and selected, it should be noted that the search was conducted between September 1 and 30, 2025.

Thus, the processing and analysis of the selected bibliographic material occurred through detailed reading and subsequent preparation of research notes, which enabled, in addition to the identification of other bibliographic materials relevant to the study, the further exploration of the topic in question for the application of exploratory and descriptive methods.

Furthermore, because this is a relatively new topic with an apparent scarcity of publications, according to the search parameters employed, scientometrics of the selected articles was performed, consisting of a quantitative exploration of the material, in which the following data were mapped: areas of study (according to the scope of the journals), publication dates (year), and publication locations (countries).

Results Discussion

The data made it possible to describe the main advances and limitations of the use of AI in the reviewed literature, as well as to explore the results of other authors in order to compare them with traditional methods and understand the advances and limitations of emerging technologies in water resources monitoring in the face of critical hydrological events in different uses.

In methodological terms, although limited by the temporal range, the research made it possible to present an overview of academic production on the use of AI in water resources management. First, the results were described, beginning with real-time monitoring and optimization, followed by the need for innovation, since these were the most apparent situations in the discussions and results of the reviewed studies.

WRM is urgent in view of persistent scarcity, the imbalance between supply and demand, and the intensification of critical hydrological events, such as floods and droughts, which generate risks to life and economic losses (Yang & Liu 2020). Although fundamental, water is a limited resource (Yang & Liu 2020; Durgun 2024), making the use of hydrological models necessary to support WQM and the prevention of floods and scarcity.

WQM has historically been based on traditional laboratory methods, with samples collected and transported by trained personnel for subsequent analysis (Paepae et al. 2021). Although they provide high precision and standardization for regulatory purposes (Zhuiykov 2012; Murphy et al. 2015), including in recent approaches, these methods reveal limitations in dynamic contexts and hydrological crises, such as high costs, dependence on equipment and specialists, sampling errors, operational failures, lack of real-time data, and low effectiveness against emerging contaminants, such as pharmaceuticals (Gholizadeh et al. 2016; Yaroshenko et al. 2020; Paepae et al. 2021).

Furthermore, despite advances in the use of WSNs with portable sensors (Paepae et al. 2021), these technologies still present limitations, such as high energy demand, vulnerability to cyberattacks, and high installation costs (Pulé et al. 2017; Jan et al. 2021).

In this context, the literature indicated that the search for more robust, efficient, and stable technologies drove the rise of AI, ML, and IoT, which are now essential to the digital transformation of water and Industry 4.0 (Matheri et al. 2022). AI acts to simplify and accelerate complex processes, especially in WWT (Alharbi 2024), and, when associated with big data, has enabled the generation of large volumes of data from sensors and operational sampling, creating data-based opportunities for the operation and control of these systems (Blumensaat et al. 2019; Garrido-Baserba et al. 2020; Poch et al. 2020).

Next, applications of smart infrastructure are described, highlighting that the integration between IoT and AI has the potential to transform the monitoring, control, and automation of WDNs (Govinda & Saravanaguru 2016; Hammi et al. 2017; Shah & Yaqoob 2016), by providing rapid responses and strategic information to utilities to address the challenges of these systems (Velayudhan et al. 2022).

Other applications of smart infrastructure include AI-based irrigation systems, which autonomously regulate water use according to soil moisture, optimizing planning, water efficiency, and crop yields (Mgendi 2024; Kamarbekov & Baimaganbetov 2024), as well as AI support for the management of SWNs, reducing

pipeline failures and losses and increasing efficiency and sustainability (Bush & Uber 1998; Marney & Sharma 2012; Morosini et al. 2017).

Additionally, approaches such as ANNs (Bubtiena et al. 2011), NFS, and SVM (Kutyłowska 2015) are used to predict failures and assess system reliability (Asnaashari et al. 2013), while the integration of AI and IoT in WDNs has improved the use of smart sensor data (Plageras et al. 2018; Teng et al. 2019), leak detection, and cost reduction (Maamar et al. 2019).

Finally, the main challenges and limitations of the use of AI and other emerging technologies in WRM were identified. Although AI represents a significant advance, its implementation faces challenges that traditional methods, despite their shortcomings, did not have or addressed differently, such as privacy and data complexity (Pulé et al. 2017; Jan et al. 2021).

In the livestock sector, especially aquaculture, there remains a research gap regarding the environmental impacts of deploying IoT devices in aquatic ecosystems, including chemical pollution and radiation exposure (Senoo et al. 2024). Furthermore, regarding water treatability, the challenge of balancing the removal of contaminants, such as heavy metals (Chen et al. 2020) and microplastics (Iyare et al. 2020), with energy efficiency remains, especially in CWSS (Huang et al. 2023), due to technological limitations and knowledge gaps concerning the use of these technologies in WRM (McCutcheon & Mauter 2023).

Another aspect evidenced is that, although the integration between big data and AI is advancing in data analysis (Blumensaat et al. 2019; Garrido-Baserba et al. 2020), optimization based on online models is still little applied in water and wastewater treatment due to the complexity of modeling, biological dynamics, the absence of visualization techniques, and the low quality of industrial data (Matheri et al. 2022).

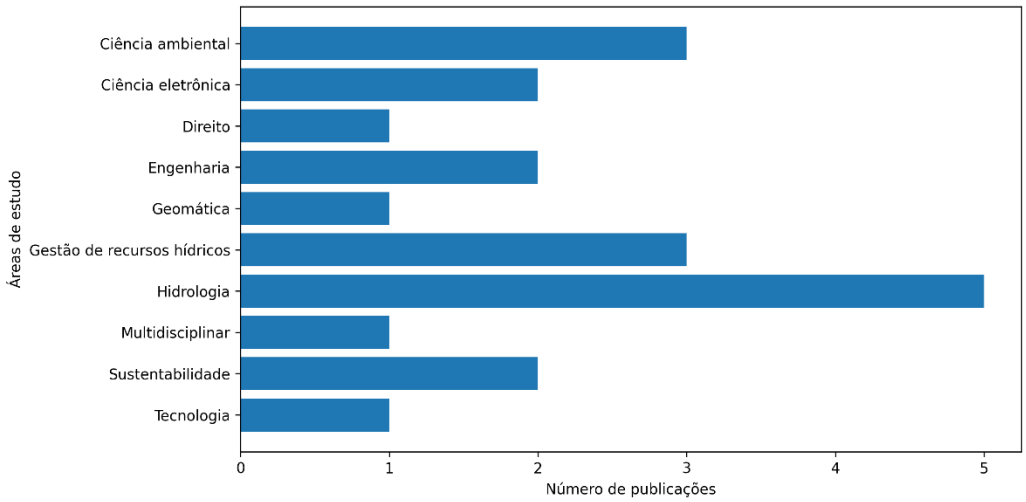
In addition, the necessary digital transformation requires interdisciplinary and sociotechnical approaches that consider not only water engineering systems but also social aspects, such as equity, legal issues, and data privacy (Poch et al. 2020). An aspect briefly addressed, but relevant to this review, concerns the importance of a comprehensive analysis of the Water-Energy Nexuses (WEN) and Water-Energy-Infrastructure-Human Nexus (WEIHN), as highlighted by Huang et al. (2023), Matheri et al. (2022), Poch et al. (2020), and Silva (2022). After all, discussing water resources monitoring implies considering human beings, who depend directly on these resources and on effective and efficient management. The digitalization wave of the 21st century, driven by cloud computing, big data, and generative AI, has established data centers as critical infrastructures that sustain the global digital economy. Their energy consumption increased from 80 TWh in 2000 to 620 TWh in 2024, currently representing 0.43% of global primary energy, with projections of reaching between 1,000 and 1,600 TWh by 2030 (Silva et al. 2026 p. 1).

Thus, it is concluded that traditional methods offer high laboratory precision (Zhuiykov 2012; Murphy et al. 2015), but present limitations in real-time response, especially for large-scale data (Gholizadeh et al. 2016; Yaroshenko et al. 2020). In contrast, AI and IoT show promise by enabling automation and continuous monitoring of resources (Velayudhan et al. 2022), although they also impose challenges related to modeling complexity (Poch et al. 2020), high energy costs and environmental impacts (Abatan et al. 2024), and the integration of sociotechnical and behavioral factors of users (Poch et al. 2020; Matheri et al. 2022).

Scientometrics of Data

As this was a bibliographic review of a topic that demonstrated scarcity in the databases searched, the scientometric method was adopted as a relevant part of the article's results. The following presents a descriptive overview of the areas of study, according to the scope of the journals of origin, which have addressed the topic.

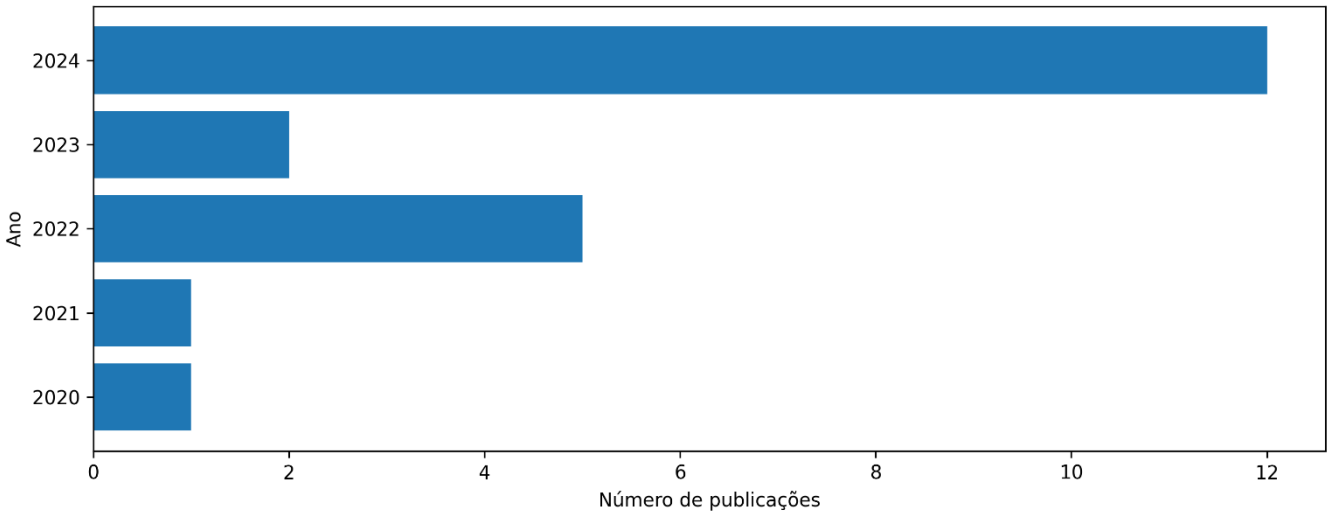
Twenty-one articles were reviewed (as shown in Graph 1), distributed, according to the scope of the journals, among the following areas of study: Environmental Science (3), Electronic Science (2), Law (1), Engineering (2), Geomatics (1), Water Resources Management (3), Hydrology (5), Multidisciplinary (1), Sustainability (2), and Technology (1). A predominance was observed of areas directly related to water resources, such as Water Resources Management and Hydrology, which together correspond to approximately 38% of the studies analyzed. In contrast, the Technology area had low representation, with only one publication, equivalent to approximately 4.8% of the total reviewed.



Graph 1: Areas of study, Authors 2025.

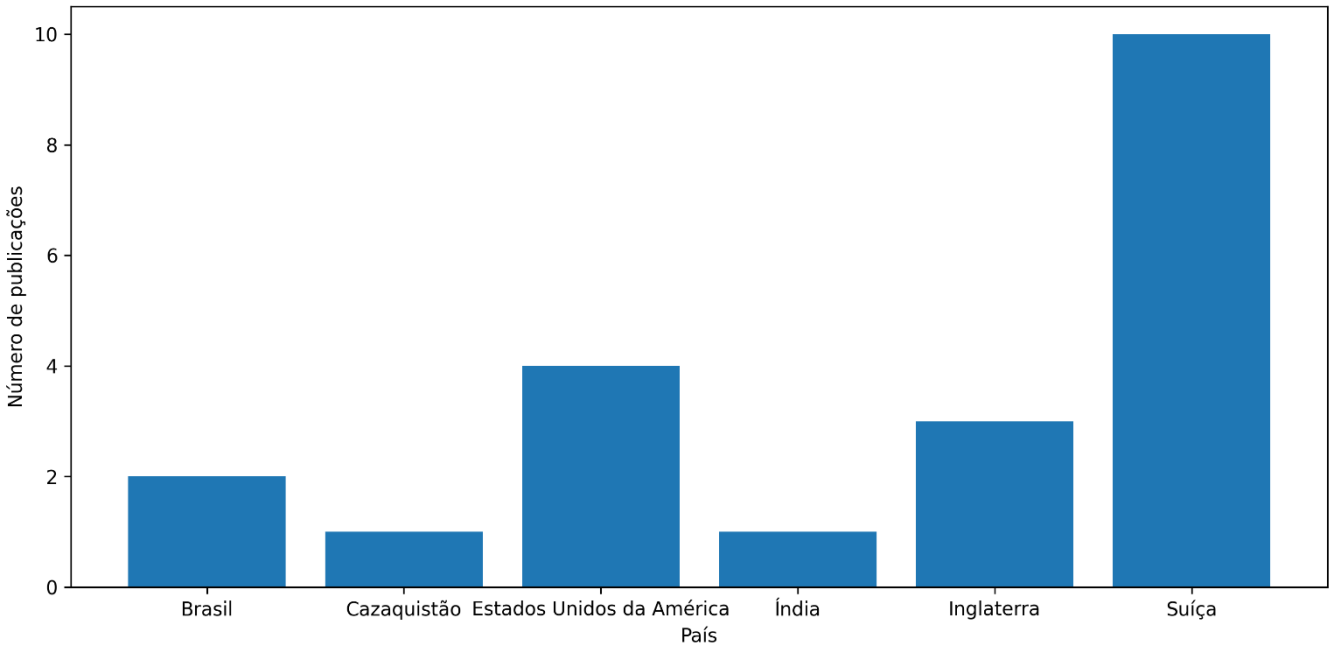
It was also found that areas related to the environmental field, Environmental Science, Water Resources Management, Hydrology, Multidisciplinary, and Sustainability, concentrate the majority of publications, totaling 14 articles, representing approximately 67% of the analyzed set. These percentages, especially with regard to the Technology area, corroborate authors' observations regarding the scarcity of studies focused on new methodologies within the WEIHN (Bethke et al. 2021) and reinforce the need for interdisciplinary approaches (Poch et al. 2020).

It should be noted, however, that this scenario also extends to other areas of knowledge, considering the small number of publications found and selected for the review. Next, the percentage distribution of publications according to periodicity is presented..



Graph 2: Publication dates (year), Authors 2025..

The temporal range of the research covered the period from 2020 to 2024 (as shown in Graph 2), in which the 21 identified publications were unevenly distributed: 2020 (1), 2021 (1), 2022 (5), 2023 (2), and 2024 (12). The small number of publications between 2020 and 2023 may be associated with the impacts of the COVID-19 pandemic, caused by the SARS-CoV-2 virus, which ended worldwide in May 2023, according to Pinelli (2023). Next, the data on the selected publications according to the countries in which they were published are presented.



Graph 3: Publication locations (country), Authors 2025..

It can be observed (as shown in Graph 3) that, unlike the previous graph, in which annual variation was associated with the COVID-19 pandemic, the majority of the studies analyzed are concentrated on the European continent, particularly Switzerland (10) and England (3), which together account for approximately 62% of the publications.

Thus, the reviewed publications were distributed according to country as follows: Brazil (2), Kazakhstan (1), United States of America (4), India (1), England (3), and Switzerland (10). Next are North America, represented by the United States of America (4), with approximately 19%, followed by South America, with Brazil (2), and Asia, with Kazakhstan (1) and India (1), both with approximately 9.5%.

Conclusion

This review analyzed the advances and limitations of the use of AI in WRM compared to traditional methods. The results indicate that the integration between AI and IoT drives the digital transformation of the water sector and provides rapid responses and automation that are essential for mitigating critical hydrological events.

However, it was found that the adoption of these technologies still faces significant bottlenecks related to modeling complexity, low quality of industrial data, and energy costs.

The main scientific contribution of this study lies in the descriptive, exploratory, and scientometric systematization of scientific production (2020–2024), by demonstrating that the technical efficiency of algorithms cannot be analyzed in isolation. The study advances the literature by overcoming a purely technocentric approach, demonstrating that the consolidation of AI in the water sector fundamentally depends on incorporating sociotechnical, human, and governmental dimensions within the WEIHN.

Based on these findings, it is suggested that future research should be guided by the integration of three fundamental areas. First, it is necessary to advance methodologically in the capture of qualitative and quantitative data on human behavior, aiming to ensure equity in access to water within the WEIHN. Second, in-depth investigation is required into the environmental sustainability of the technology itself, measuring the ecological impacts of deploying IoT devices in aquatic ecosystems and the water and energy footprint of data processing. Finally, improvement of predictive models and databases is recommended through the development of AI architectures capable of dealing with the biological dynamics of water treatment and the low quality of measurements in decentralized systems.

References

Aakash S, Valliammai A, Nagarajan M, Sivakumar SD, Baskar M, Sujitha E 2024. Conjunctive use in water resource management: Current trends and future directions. *Water Supply* 24(11):3881. [cited 2025 Sep 16]. Available from: https://doi.org/10.2166/ws.2024.215.

Abatan A, Obaigbena A, Ugwuanyi ED, Jacks BS, Sodiya EO, Daraojimba OH, Lottu OA 2024. Simulation-Driven Strategies for Enhancing Water Treatment Processes in Chemical Engineering: Addressing Environmental Challenges. *Engineering Heritage Journal (GWK)* 5(1):34–41. [cited 2025 Sep 16]. Available from: https://doi.org/10.26480/gwk.01.2024.34.41.

Adu-Manu KS, Taparello C, Heizelman W, Katsriku FA, Abdulai JD, et al 2017. Water quality monitoring using wireless sensor networks: Current trends and future research directions. *ACM Transactions on Sensor Networks* 13(1):Art. 4. [cited 2025 Sep 17]. Available from: http://dx.doi.org/10.1145/3005719.

Ahmed U, Mumtaz R, Anwar H, Mumtaz S, Qamar AM 2019a. Water quality monitoring: from conventional to emerging technologies. *Water Sci. Technol. Water Supply* 20:28–45. [cited 2025 Sep 17]. Available from: https://doi.org/10.2166/ws.2019.144.

Ahmed U, Mumtaz R, Anwar H, Shah AA, Irfan R, García-Nieto J 2019b. Efficient Water Quality Prediction Using Supervised Machine Learning. *Water* 11(2210):1–14. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/w11112210.

Almetwally SAH, Hassan MK, Mourad MH 2020. Real time Internet of Things (IoT) based water quality management system. *Procedia CIRP* 91:478-485.

Alharbi S, Felemban A, Abdelrahim A, Al-Dakhil M 2024. Agricultural and technology-based strategies to improve water-use efficiency in arid and semiarid areas. *Water* 16(13):1842. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/w16131842.

Allah AAD, Hashim NBM, Awang AB 2017. Discovering Trends of Agricultural Drought in Tihama Plain, Yemen: A Preliminary Assessment. *Indonesian Journal of Geography* 49(1):17–27. [cited 2025 Sep 18]. Available from: http://dx.doi.org/10.22146/ijg.12089.

American Meteorological Society (AMS) 2004. Statement on meteorological drought. *Bull. Am. Meteorol. Soc.* 85:771–773.

Archer DR, Fowler HJ 2018. Flash flood response to intense rainfall in Britain. *J. Flood Risk Manage* 11:S121–S133. [cited 2025 Sep 16]. Available from: https://doi.org/10.1111/jfr3.12187.

Asnaashari A, McBean EA, Gharabaghi B, Tutt D 2013. Forecasting watermain failure using artificial neural network modelling. *Canadian Water Resources Journal* 38(1):24–33.

Assimakopoulos F, Vassilakis C, Margaris D, Kotis K, Spiliotopoulos D 2024. Artificial intelligence tools for the agriculture value chain: Status and prospects. *Electronics* 13(22):4362. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/electronics13224362.

Bakker K 2012. Water Security: Research Challenges and Opportunities. *Science* 337(6097):914–915.

Bakker K, Cook C 2011. Water governance in Canada: innovation and fragmentation. *International Journal of Water Resources Development* 27(2):275–289.

Below R, Wirtz A, Guha-Sapir D 2009. *Disaster Category Classification and Peril Terminology for Operational Purposes*. Centre for Research on the Epidemiology of Disasters, Brussels, Belgium. (Working paper, 264).

Bethke GM, Cohen AR, Stillwell AS 2021. Emerging investigator series: disaggregating residential sector high-resolution smart water meter data into appliance end-uses with unsupervised machine learning. *Environ. Sci.: Water Res. Technol.* 7:487. [cited 2025 Sep 17]. Available from: https://doi.org/10.1039/d0ew00724b.

Blumensaat F, Leitão JP, Ort C, Rieckermann J, Scheidegger A, Vanrolleghem PA, Villez K 2019. How Urban Storm- and Wastewater Management Prepares for Emerging Opportunities and Threats: Digital Transformation, Ubiquitous Sensing, New Data Sources, and Beyond - A Horizon Scan. *Environmental Science & Technology* 53:8488–8498. [cited 2025 Sep 16]. Available from: https://doi.org/10.1021/acs.est.8b06481.

Boons F, Montalvo C, Quist J, Wagner M 2013. Sustainable innovation, business models and economic performance: an overview. *Journal of Cleaner Production* 45:1–8.

Boretti A, Rosa L 2019. Reassessing the projections of the world water development report. *NPJ Clean Water* 2(1):15. [cited 2025 Sep 17]. Available from: https://doi.org/10.1038/s41545-019-0039-9.

Bubtiena AM, Elshafie AH, Jafaar O 2011. Application of artificial neural networks in modeling water networks. In *Proceedings of the 7th International Colloquium on Signal Processing and Its Applications*, Penang, Malaysia, p. 50-57.

Bush CA, Uber JG 1998. Sampling design methods for water distribution model calibration. *Journal of Water Resources Planning and Management* 124(6):334–344.

Cenci DR, Beck CAMR, Boff MM 2023. Cidades inteligentes, inteligência artificial e os desafios na pandemia COVID-19: a criação de big data para vigilância, controle e segregação socioespacial da população marginalizada. *Revista de Direito da Cidade* 15(4):1810–1843. [cited 2025 Sep 16]. Available from: https://doi.org/10.12957/rdc.2023.65722.

Chapman D 1996. Water Quality Assessments: A Guide to Use of Biota, Sediments and Water in Environmental Monitoring. 2. ed. CRC Press, London, UK.

Chen Y, Song L, Liu Y, Yang L, Li D 2020. A Review of the Artificial Neural Network Models for Water Quality Prediction. *Applied Sciences* 10(17):5776. [cited 2025 Sep 18]. Available from: https://doi.org/10.3390/app10175776.

Clark RM 2014. Securing water and wastewater systems: global perspectives. *Water and Environment Journal* 28:449–458. [cited 2025 Sep 17]. Available from: https://doi.org/10.1111/wej.12078.

Dai J, Wu S, Han G, Weinberg J, Xie X, Wu X, Song X, Jia B, Xue W, Yang Q 2018. Water-energy nexus: A review of methods and tools for macro-assessment. *Applied Energy*. [cited 2025 Sep 18]. Available from: https://doi.org/10.1016/j.apenergy.2017.08.243.

Department of Water Affairs and Forestry (South Africa) 1996. *South African Water Quality Guidelines*. 2. ed. Vol. 1, Domestic Use, Pretoria.

Dixit F, Barbeau B, Ghavam Mostafavi S, Mohseni M 2019. PFOA and PFOS removal by ion exchange for water reuse and drinking applications: role of organic matter characteristics. *Environ. Sci.: Water Res. Technol.* 5:1782–1795. [cited 2025 Sep 16]. Available from: https://doi.org/10.1039/c9ew00409b.

Du Plessis A, Du Plessis A 2019. Primary water quality challenges, contaminants and the world's dirtiest places. In *Water as an Inescapable Risk: Current Global Water Availability, Quality and Risks with a Specific Focus on South Africa*. p. 79–114. [cited 2025 Sep 18]. Available from: https://doi.org/10.1007/978-3-030-03186-2_5.

Durgun Y 2024. Real-time water quality monitoring using AI-enabled sensors: Detection of contaminants and UV disinfection analysis in smart urban water systems. *Journal of King Saud University-Science* 36:103409. [cited 2025 Sep 16]. Available from: https://doi.org/10.1016/j.jksus.2024.103409.

El Bilali A, Taleb A 2024. State-of-the-art-on irrigation water quality management using data-driven methods: Practical application, limitations, and prospective directions. *Physics and Chemistry of the Earth* 136:103794. [cited 2025 Sep 16]. Available from: https://doi.org/10.1016/j.pce.2024.103794.

Elimelech M, Phillip WA 2011. The Future of Seawater Desalination: Energy, Technology, and the Environment. *Science* 333(6043):712. [cited 2025 Sep 17]. Available from: https://doi.org/10.1126/science.1200488.

Falconer RH, Cobby D, Smyth P, Astle G, Dent J, Golding B 2009. Pluvial flooding: New approaches in flood warning, mapping and risk management. *J. Flood Risk Manag.* 2:198–208.

Food and Agriculture Organization (FAO) 2021 [homepage on the Internet]. *AQUASTAT: FAO's Global Information System on Water and Agriculture*. [cited 2025 Sep 17]. Available from: http://www.fao.org/aquastat/en/overview/methodology/water-use.

Gaffoor TA 2017. *Real-time control and optimization of water supply & distribution infrastructure*. Dissertação de Mestrado, University of Waterloo, Waterloo, 216 pp.

García EA, Agulló-Barceló M, Bond P, Keller J, Gernjak W, Radjenovic J 2018. Hybrid electrochemical-granular activated carbon system for the treatment of greywater. *Chem. Eng. J.* 352:405–411.

Garrido-Baserba M, Corominas L, Cortés U, Rosso D, Poch M 2020. The Fourth-Revolution in the Water Sector Encounters the Digital Revolution. *Environmental Science & Technology* 54:4698–4705. [cited 2025 Sep 17]. Available from: https://doi.org/10.1021/acs.est.9b04251.

Gholizadeh MH, Melesse AM, Reddi L 2016. A Comprehensive Review on Water Quality Parameters Estimation Using Remote Sensing Techniques. *Sensors* 16(8):1298. [cited 2025 Sep 18]. Available from: https://doi.org/10.3390/s16081298.

Gibbs WJ 1975. Drought - its definition, delineation and effects. In World Meteorological Organization (WMO). *Drought: Lectures presented at the twenty-sixth session of the WMO Executive Committee*. WMO, Geneva, p. 1–40. [cited 2025 Sep 18]. Available from: https://docslib.org/doc/1406976/drought-its-definition-delineation-and-effects-by-w.

Govinda K, Saravanaguru R 2016. Review on IoT technologies. *Int. J. Appl. Eng. Res.* 11(4):2848–2853.

Guo Y, Huang S, Huang Q, Wang H, Fang W, Yang Y, Wang L 2019. Assessing socioeconomic drought based on an improved Multivariate Standardized Reliability and Resilience Index. *Journal of Hydrology*. [cited 2025 Sep 17]. Available from: https://doi.org/10.1016/j.jhydrol.2018.11.055.

Hamdy A, Ragab R, Scarascia-Mugnozza E 2003. Coping with water scarcity: water saving and increasing water productivity. *Irrig. and Drain.* 52:3–20.

Hammi B, Khatoun R, Zeadally S, Fayad A, Khoukhi L 2017. Internet of Things (IoT) technologies for smart cities. *IET Netw.* 7(1):1–13. [cited 2025 Sep 16]. Available from: https://doi.org/10.1049/iet-net.2017.0163.

Hasan HH, Razali SFM, Muhammad NS, Ahmad A 2019. Research Trends of Hydrological Drought: A Systematic Review. *Water (Switzerland)* 11(2252). [cited 2025 Sep 18]. Available from: https://doi.org/10.3390/w11112252.

Huang Y, Zhang J, Ren Z, Xiang W, Sifat I, Zhang W, Zhu J, Li B 2023. Next generation decentralized water systems: a water-energy-infrastructure-human nexus (WEIHN) approach. *Environ. Sci.: Water Res. Technol.* 9:2446–2471. [cited 2025 Sep 16]. Available from: https://doi.org/10.1039/d3ew00506b.

Hurford AP, Priest SJ, Parker DJ, Lumbroso DM 2011. The effectiveness of extreme rainfall alerts in predicting surface water flooding in England and Wales. *International Journal of Climatology*. Available from: https://doi.org/10.1002/joc.2391.

Iyare PU, Ouki SK, Bond T 2020. Microplastics removal in wastewater treatment plants: a critical review. *Environ. Sci.: Water Res. Technol.* 6:2664–2675.

Jan F, Min-Allah N, Düştegör D 2021. IoT Based Smart Water Quality Monitoring: Recent Techniques, Trends and Challenges for Domestic Applications. *Water* 13(13):1729. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/w13131729.

Jia Y, Zheng F, Maier HR, Ostfeld A, Creaco E, Savic D, Langeveld J, Kapelan Z 2021. Water quality modeling in sewer networks: Review and future research directions. *Water Res.* 202:117419.

Joseph K, Sharma AK, Van Staden R 2022. Development of an Intelligent Urban Water Network System. *Water* 14(9):1320. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/w14091320.

Kamarbekov GM, Baimaganbetov AYe 2024. Using artificial intelligence for hydrological modelling. *Geography and Water Resources* 1:58-62. [cited 2025 Sep 16]. Available from: https://doi.org/10.55764/2957-9856/2024-1-58-62.8.

Kaźmierczak A, Cavan G 2011. Surface water flooding risk to urban communities: Analysis of vulnerability, hazard and exposure. *Landscape and Urban Planning* 103:185–197. [cited 2025 Sep 17]. Available from: https://doi.org/10.1016/j.landurbplan.2011.07.008.

Kesarwani M, Neeti N, Chowdary VM 2023. Evaluation of Different Gridded Precipitation Products for Drought Monitoring: A Case Study of Central India. *Theor. Appl. Climatol.* 151:817–841.

Kutyłowska M 2015. Neural network approach for failure rate prediction. *Engineering Failure Analysis* 47:41–48.

Lakho FH, Le HQ, Mattheeuws F, Igodt W, Depuydt V, Desloover J, Rousseau DPL, Van Hulle SWH 2021. Decentralized grey and black water reuse by combining a vertical flow constructed wetland and membrane based potable water system: Full scale demonstration. *J. Environ. Chem. Eng.* 9:104688.

Lueth KL 2019. *State of the IoT 2020: 12 Billion Iot Connections, Surpassing Non-IoT for the First Time*. [cited 2025 Sep 18]. Available from: https://iot-analytics.com/state-of-the-iot-2020-12-billion-iot-connections-surpassing-non-iot-for-the-first-time/.

Maamar Z, Baker T, Faci N, Al-Khafajiy M, Ugljanin E, Atif Y, Sellami M 2019. Weaving cognition into the Internet-of-Things: application to water leaks. *Cogn. Syst. Res.* 56:233–245.

Machell J, Prior K, Allan R, Andresen JM 2015. The water energy food nexus – challenges and emerging solutions. *Environ. Sci.: Water Res. Technol.* 1:15.

Manavalan E, Jayakrishna K 2019. A review of Internet of Things (IoT) embedded Sustainable Supply Chain for Industry 4.0 requirements. *Computers & Industrial Engineering*. [cited 2025 Sep 17]. Available from: https://doi.org/10.1016/j.cie.2018.11.030.

Mancosu N, Snyder RL, Kyriakakis G, Spano D 2015. Water Scarcity and Future Challenges for Food Production. *Water* 7(3):975–992. [cited 2025 Sep 18]. Available from: https://doi.org/10.3390/w7030975.

Manyika J 2015. *The internet of things: mapping the value beyond the hype*. McKinsey Global Institute, Washington, DC.

Marney D, Sharma A 2012. The application and utility of 'smarts' for monitoring water and its infrastructure. *Water: J. Aust. Water Assoc.* 39:86–92.

Matheri AN, Eloko SN, Ntuli F, Ngila JC 2020. Influence of pyrolyzed sludge use as an adsorbent in removal of selected trace metals from wastewater treatment. *Case Studies in Chemical and Environmental Engineering* 2:100018. [cited 2025 Sep 17]. Available from: https://doi.org/10.1016/j.cscee.2020.100018.

Matheri AN, Mohamed B, Ntuli F, Nabadda E, Ngila JC 2022. Sustainable circularity and intelligent data-driven operations and control of the wastewater treatment plant. *Physics and Chemistry of the Earth* 126:103152. [cited 2025 Sep 16]. Available from: https://doi.org/10.1016/j.pce.2022.103152.

McCutcheon JR, Mauter MS 2023. Fixing the desalination membrane pipeline. *Science* 380:242–244.

Mgendi G 2024. Unlocking the potential of precision agriculture for sustainable farming. *Discover Agriculture* 2:87. [cited 2025 Sep 16]. Available from: https://doi.org/10.1007/s44279-024-00078-3.

Mishra AK, Singh VP 2010. A review of drought concepts. *Journal of Hydrology* 391:202–216. [cited 2025 Sep 18]. Available from: https://doi.org/10.1016/j.jhydrol.2010.07.012.

Morosini FA, Caruso O, Costanzo F, Savic D 2017. Emergency management of water distribution systems: the nodal demand control. *Procedia Engineering* 186:428–435.

Murphy K, Heery B, Sullivan T, Zhang D, Paludetti L, Lau KT, Diamond D, Costa E, O'Connor N, Regan F 2015. A low-cost autonomous optical sensor for water quality monitoring. *Talanta* 132:520–527. [cited 2025 Sep 18]. Available from: https://doi.org/10.1016/j.talanta.2014.09.045.

Nações Unidas Brasil [homepage on the Internet]. Objetivos de Desenvolvimento Sustentável. [cited 2025 Dec 19]. Available from: https://brasil.un.org/pt-br/sdgs.

Narendran S, Pradeep P, Ramesh MV 2017. An Internet of Things (IoT) based sustainable water management. In *IEEE Global Hum. Technol. Conf. (GHTC)*. p. 1–6.

Ngila JC, Matheri AN, Muckoya V, Ngigi E, Ntuli F, Seodigeng T, Zvinowanda C 2020. *Mathematical modelling for biological wastewater treatment plants, Gauteng, South Africa*. Water Research Commission, Gauteng, 207 pp. (WRC Report No 2563/1/19).

Paepae T, Bokoro PN, Kyamakya K 2021. From fully physical to virtual sensing for water quality assessment: A comprehensive review of the relevant state-of-the-art. *Sensors* 21(21):6971. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/s21216971.

Pan SY, Snyder SW, Lina JY, Chiang PC 2018. Electrokinetic desalination of brackish water and associated challenges in the water and energy nexus. *Environ. Sci.: Water Res. Technol.* [cited 2025 Sep 18]. Available from: https://doi.org/10.1039/C7EW00550D.

Partzsch L 2009. Smart regulation for water innovation – the case of decentralized rainwater technology. *Journal of Cleaner Production* xxx:1–7.

Pinelli N 2023. OMS decreta o fim da emergência de saúde global causada pela Covid-19. *Butantan: Notícias* [serial on the Internet]. [cited 2025 Sep 18]. Available from: https://butantan.gov.br/noticias/oms-decreta-o-fim-da-emergencia-de-saude-global-causada-pela-covid-19.

Plageras AP, Psannis EK, Stergiou C, Wang H, Gupta BB 2018. Efficient IoT-based sensor BIG Data collection-processing and analysis in Smart Buildings. *Future Generation Computer Systems*. Available from: https://doi.org/10.1016/j.future.2017.09.082.

Poch M, Garrido-Baserba M, Corominas L, Perelló-Moragues A, Monclús H, Cermerón-Romero M, Melitas N, Jiang SC, Rosso D 2020. When the fourth water and digital revolution encountered COVID-19. *Science of the Total Environment* 744:140980. [cited 2025 Sep 17]. Available from: https://doi.org/10.1016/j.scitotenv.2020.140980.

Pulé M, Yahya A, Chuma J 2017. Wireless sensor networks: A survey on monitoring water quality. *Journal of Applied Research and Technology* 15:562–570. [cited 2025 Sep 18]. Available from: https://doi.org/10.1016/j.jart.2017.07.004.

Rabaey K, Vandekerckhove T, de Walle AV, Sedlak DL 2020. The third route: Using extreme decentralization to create resilient urban water systems. *Water Res.* 185:116276.

Robles T, Alcarria R, Martín D, Navarro M, Calero R, Iglesias S, López M 2015. An IoT based reference architecture for smart water management processes. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications* 6(1):4–23.

Schubert SD, et al 2016. Global Meteorological Drought: A Synthesis of Current Understanding with a Focus on SST Drivers of Precipitation Deficits. *Journal of Climate* 29:3989–4019. [cited 2025 Sep 18]. Available from: https://doi.org/10.1175/JCLI-D-15-0452.1.

Senoo EEK, Anggraini L, Kumi JA, Karolina LB, Akansah E, Sulyman HA, Mendonça I, Aritsugi M 2024. IoT solutions with artificial intelligence technologies for precision agriculture: Definitions, applications, challenges, and opportunities. *Electronics* 13(10):1894. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/electronics13101894.

Shah SH, Yaqoob I 2016. A survey: Internet of Things (IoT) technologies, applications and challenges. In *IEEE International Conference on Smart Energy Grid Engineering*.

Sheffield J, Wood EF 2011. *Drought: Past and Future Scenarios*. Earthscan, London, UK.

Silva LA, Vasconcelos ES, Paiva LFR, Goulart CS, Joaquim WM, Elias MEP, Teixeira EP, Collaço MHVR 2026. Consumo de Energia em Data Centers e Estratégias de Eficiência: Uma Revisão da Literatura. *Revista de Engenharia, TI e Inovação* 3(1):1-17. [cited 2026 Sep 10]. Available from: https://doi.org/10.31496/retii.v3i1.2038.

Silva JA 2022. Implementation and integration of sustainability in the water industry: A systematic literature review. *Sustainability* 14(23):15919. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/su142315919.

Sindhu VK, Singh S, Brar S 2024. Water resource scenario in Punjab: Challenges and technological interventions for sustainable use in agriculture. *Agricultural Research Journal* 61(4):483–498. [cited 2025 Sep 16]. Available from: https://doi.org/10.5958/2395-146X.2024.00062.0.

Sorbello J, Marck R 2014. Applications for intelligent water network systems. *Water: J. Aust. Water Assoc.* 41:75–80.

Tarate SB, Patel NR, Danodia A, Pokhariyal S, Parida BR 2024. Geospatial Technology for Sustainable Agricultural Water Management in India—A Systematic Review. *Geomatics* 4(2):91–123. [cited 2025 Sep 16]. Available from: https://doi.org/10.3390/geomatics4020006.

Teng H, Liu Y, Liu A, Xiong NN, Cai Z, Wang T, Liu X 2019. A novel code data dissemination scheme for Internet of Things through mobile vehicle of smart cities. *Future Generation Computer Systems* 94:351-367.

United Nations Secretariat General 1994. United Nations Convention to Combat Drought and Desertification in Countries Experiencing Serious Droughts and/or Desertification, Particularly in Africa. UN Secretariat General, Paris.

Vakilifard N, Anda M, Bahri PA, Ho G 2018. The role of water-energy nexus in optimising water supply systems – Review of techniques and approaches. *Renewable and Sustainable Energy Reviews*. [cited 2025 Sep 18]. Available from: https://doi.org/10.1016/j.rser.2017.05.125.

Van Loon AF 2015. Hydrological drought explained. *WIREs Water* 2:359–392. [cited 2025 Sep 18]. Available from: https://doi.org/10.1002/wat2.1085.

Van Loosdrecht MCM, Brdjanovic D 2014. Anticipating the next century of wastewater treatment: advances in activated sludge sewage treatment can improve its energy use and resource recovery. *Science* 344(6191):1452–1453. [cited 2025 Sep 17]. Available from: https://doi.org/10.1126/science.1255183.

Velayudhan NK, Pradeep P, Rao SN, Devidas AR, Ramesh MV 2022. IoT-Enabled Water Distribution Systems-A Comparative Technological Review. *IEEE Access* 10:101042-101070. [cited 2025 Sep 16]. Available from: https://doi.org/10.1109/ACCESS.2022.3208142.

Verde Neto JC, Souza Filho FA 2022. Metodologia para a construção de uma política pública de inovação tecnológica em recursos hídricos: Da construção da agenda a decisão organizacional. *Revista de Gestão de Água da América Latina* 19:e5. [cited 2025 Sep 16]. Available from: https://doi.org/10.21168/rega.v19e5.

Wali SU, Usman AA, Usman AB, Abdullahi U, Mohammed IU, Hayatu JM 2024. Impact of geology on hydrogeological and hydrochemical characteristics of groundwater in tropical environments: a narrative review. *International Journal of Hydrology* 8(6):202–221. [cited 2025 Sep 16]. Available from: https://doi.org/10.15406/ijh.2024.08.00392.

Wolf J 2008. Coastal Flooding – Impacts of coupled wave-surge-tide models. *Advances in Geosciences* 17:19–23. [cited 2025 Sep 16]. Available from: https://doi.org/10.5194/adgeo-17-19-2008.

Woodruff JD, Irish JL, Camargo SJ 2013. Coastal flooding by tropical cyclones and sea-level rise. *Nature* 504(7478):44–52. [cited 2025 Sep 16]. Available from: https://doi.org/10.1038/nature12855.

World Meteorological Organization (WMO) 1986. *Report on Drought and Countries Affected by Drought During 1974–1985*. WMO, Geneva, Switzerland, 118 pp.

Yang TH, Liu WC 2020. A general overview of the risk-reduction strategies for floods and droughts. *Sustainability* 12(7):2687. [cited 2025 Sep 18]. Available from: https://doi.org/10.3390/su12072687.

Yaroshenko I, Kirsanov D, Marjanovic M, Lieberzeit PA, Korostynska O, Mason A, Frau I, Legin A 2020. Real-Time Water Quality Monitoring with Chemical Sensors. *Sensors* 20(12):3432. [cited 2025 Sep 18]. Available from: https://doi.org/10.3390/s20123432.

Zhuiykov S 2012. Solid-state sensors monitoring parameters of water quality for the next generation of wireless sensor networks. *Sensors and Actuators B: Chemical* 161:1–20. [cited 2025 Sep 16]. Available from: https://doi.org/10.1016/j.snb.2011.10.078.