UNIVERSIDAD NACIONAL DE SAN MARTIN

RCSI
https://revistas.unsm.edu.pe/index.php/rcsi
e-ISSN: 2709-992X

Review article
Artículo de revisión
Jan-Jun, 2025

Intelligent optimization of rural water infrastructure through big data and predictive models: Insights from Latin America

Optimización inteligente de la infraestructura hídrica rural con big data y predicción: Evidencias para Latinoamérica

Noriega-Murrieta, Javier[1*]

[1]Graduate School, Universidad César Vallejo, Tarapoto Campus, Peru

Received: 01 Nov. 2024 | **Accepted:** 10 Jan. 2025 | **Published:** 20 Jan. 2025

Corresponding author*: javiernm@ucvvirtual.edu.pe

How to cite this article: Noriega-Murrieta, J. (2025). Intelligent optimization of rural water infrastructure through big data and predictive models: Insights from Latin America: Insights from Latin America. *Revista Científica de Sistemas e Informática, 5*(1), e762. https://doi.org/10.51252/rcsi.v5i1.762

ABSTRACT

Access to potable water in rural areas continues to face structural challenges due to technological, operational, and planning gaps. In this study, we reviewed the state of the art on the use of Big Data and Artificial Intelligence for optimizing rural water infrastructure. We conducted a systematic review using the Scopus database, covering publications from 2015 to 2025. We identified 582 articles, of which 48 met the inclusion criteria. Our results show that predictive models and massive data analysis have improved operational efficiency by anticipating failures in distribution networks with up to 85% accuracy, thereby reducing losses. Additionally, technologies such as IoT sensors, digital twins, and automated systems have been successfully implemented in various countries, generating positive impacts on service sustainability. We conclude that the digitalization of potable water management, through AI and Big Data, constitutes an effective strategy to enhance the resilience and quality of supply in rural settings. These findings provide key inputs for designing policies and technological solutions applicable to regions such as San Martín, Peru.

Keywords: algorithms; digitalization; monitoring; supply; sustainability

RESUMEN

El acceso al agua potable en zonas rurales sigue presentando desafíos estructurales debido a brechas tecnológicas, operativas y de planificación. Este estudio revisamos el estado del arte sobre el uso de Big Data e Inteligencia Artificial en la optimización de la infraestructura hídrica rural. Realizamos una revisión sistemática en las bases de datos Scopus abarcando publicaciones entre 2015 y 2025. Identificamos 582 artículos, de los cuales 48 cumplieron con los criterios de inclusión. Los resultados mostraron que los modelos predictivos y el análisis de datos masivos han mejorado la eficiencia operativa, anticipando fallas en redes de distribución con una precisión de hasta 85%, reduciendo pérdidas. Asimismo, tecnologías como sensores IoT, gemelos digitales y sistemas automatizados han sido aplicadas con éxito en diversos países, generando impactos positivos en la sostenibilidad del servicio. Concluimos que la digitalización de la gestión del agua potable, mediante IA y Big Data, constituye una estrategia efectiva para mejorar la resiliencia y calidad del abastecimiento en contextos rurales. Estos hallazgos ofrecen insumos clave para diseñar políticas y soluciones tecnológicas aplicables en regiones como San Martín, Perú.

Palabras clave: abastecimiento; algoritmos; digitalización; monitoreo; sostenibilidad

1. INTRODUCTION

Universal access to potable water remains a global challenge, particularly in rural regions where water infrastructure faces significant limitations. Despite ongoing efforts to improve water supply, issues such as deforestation, population growth, and the lack of investment in advanced technologies continue to affect the sustainability of this resource (Esquivel-Ayala & Tapia-Cabrera, 2021). In Latin America, access to potable water reveals critical gaps due to the absence of technological tools that optimize its management, resulting in inefficient distribution, water losses, and inadequate monitoring of water quality (Martinez et al., 2018; Medina et al., 2022). These challenges are exacerbated in rural areas, where infrastructure tends to be outdated, maintenance is irregular, and access to technical expertise is limited. Moreover, climate variability and extreme weather events further threaten the availability and reliability of water services. Addressing these issues requires innovative and scalable solutions that go beyond traditional approaches, incorporating digital technologies, data-driven decision-making, and multi-stakeholder collaboration to ensure long-term sustainability and equitable access.

The San Martín region in Peru exemplifies this issue. According to the Regional Sanitation Plan of San Martín, 12.2% of the population depends on unsafe water sources, exposing thousands of people to health risks and limiting their socioeconomic development (Martinez et al., 2018). Furthermore, the lack of digitalization in potable water management has led to operational inefficiencies that hinder the delivery of efficient and equitable services. In this context, digital transformation and the use of tools based on Artificial Intelligence (AI) and Big Data emerge as key solutions for optimizing water infrastructure. Therefore, a relevant research question arises: How can predictive models and Big Data contribute to the optimization of potable water infrastructure in rural areas?

Globally, the application of predictive models and massive data analysis in potable water management remains limited, resulting in various gaps in the infrastructure and operation of these systems (J. Pandey & Verma, 2022; Sánchez Calle et al., 2021). One of the main shortcomings is the absence of real-time monitoring in distribution networks, which prevents timely detection of leaks, breakdowns, or changes in water quality (Alselek et al., 2022; Canahuire-Robles et al., 2023; Medina et al., 2022; Strobl et al., 2006). In rural areas, water supply systems are typically monitored manually, delaying the identification of failures and hindering the implementation of timely corrective measures (Amini & Dziedzic, 2022; Cheng et al., 2024; Del-Águila-Chávez et al., 2024).

Another critical gap is the lack of integration and analysis of operational data. The fragmentation of information across small local operators hinders effective evaluation of water system conditions, limiting the ability of managers to make informed decisions (Rego et al., 2024). The World Bank has identified that the absence of centralized data in potable water management complicates the detection of consumption patterns, resource planning, and the prediction of water crises (Kyritsakas et al., 2023).

Likewise, the lack of digitalization has led to a reactive rather than preventive response to water supply issues. In many rural communities, the failure of a pump or pipeline can leave the population without water for days or even weeks while repairs are identified and managed (Da Silva et al., 2014). In contrast, the use of AI-based predictive models could anticipate failures before they occur, optimizing maintenance processes and reducing downtime (de Almeida et al., 2025).

In response to these gaps, numerous studies suggest that the incorporation of Artificial Intelligence and Big Data can radically transform potable water management—even in rural contexts—toward a more efficient, predictive, and sustainable model. In general terms, the digitalization of the water sector is seen as a game changer in addressing challenges such as aging infrastructure, increasing demand, and extreme climate events. Digital technologies (IoT sensors, data analytics, AI/ML) enable a shift from reactive to preventive approaches, optimizing both the supply side (production/distribution) and the demand side (efficient consumption). This leads us to ask: What are the main emerging technologies applied in potable water management, and what impact do they have on system efficiency?

With regard to water quality, Big Data and AI offer significant improvements in monitoring and control (Bonilla et al., 2022). Real-time analytics from quality sensors (turbidity, chlorine, pH) can trigger early warnings in response to deviations indicating potential contamination, allowing us to activate response protocols before non-compliant water reaches end users. Moreover, advanced algorithms can correlate data from multiple sources—local sensors, satellite imagery, and meteorological information—to predict risks to water quality. For instance, we can anticipate turbidity episodes following heavy rainfall or detect trends of saline intrusion in coastal aquifers (Ao et al., 2025).

The evidence we have gathered indicates that the lack of adoption of AI and Big Data in rural potable water management has perpetuated significant gaps in the sustainability and efficiency of these services. Poorly monitored infrastructure, limited data availability, and reactive practices have undermined efforts to ensure safe water for the most vulnerable populations. However, recent technological advances offer concrete solutions to these challenges. The integration of sensors and IoT allows us to illuminate previously "invisible" systems, providing valuable real-time data for better resource management. In turn, artificial intelligence enables predictive models that can revolutionize planning and operations—from anticipating failures to balancing supply and demand and protecting water quality. It is important to emphasize that technology alone is not sufficient; it must be embedded within comprehensive strategies. This requires investment in digital infrastructure, training of system operators, regulatory frameworks that promote innovation, and appropriate financing mechanisms tailored to rural contexts. This leads us to our final research question: What strategies have been developed in other countries to improve potable water management through artificial intelligence and data analytics?

2. MATERIALS AND METHODS

To carry out this systematic review, we conducted a search and selection process using the Scopus database between October 2024 and January 2025, employing keywords aligned with our research questions. For the optimization of infrastructure through predictive models and Big Data, we used terms such as "Predictive analytics in water management", "Big Data for water supply", and "Machine Learning in water distribution", retrieving 230 articles. To identify emerging technologies in potable water management, we used terms such as "Smart water networks", "Artificial Intelligence in water infrastructure", and "IoT for water quality monitoring", which yielded 195 articles. Finally, to analyze strategies implemented in other countries, we searched for studies using terms such as "Data-driven decision making in water utilities" and "AI-based water management strategies", retrieving 157 articles.

To ensure the relevance of the selected studies, we applied inclusion and exclusion criteria. We included peer-reviewed articles published in indexed scientific journals between 2019 and 2025; studies focused on predictive models, artificial intelligence, or Big Data applied to potable water management; and case studies on infrastructure optimization in rural settings. We excluded theoretical studies without practical applications, articles addressing water quality without connection to infrastructure or predictive models, duplicate studies, and conference papers with low impact or lacking peer review.

Following our search strategy and established criteria, the article selection process was conducted in three stages. First, we retrieved 582 articles in the initial search. Then, we excluded 341 articles that were not directly related to the objectives of our study. Finally, we reviewed the remaining studies, applying the inclusion and exclusion criteria, and selected 48 articles for in-depth analysis.

We categorized the 48 selected articles into three main areas based on our research questions. Twenty-two articles examined the use of machine learning, predictive models, and AI in potable water management, highlighting studies on leak prediction, supply optimization, and preventive maintenance. Eighteen articles addressed solutions such as IoT sensor networks, digital twins, and intelligent monitoring systems, with successful case studies in India, Argentina, and Spain. Fourteen articles explored digitalization strategies in water management, analyzing government programs and innovation projects in Latin America, Asia, and Africa.

3. RESULTS AND DISCUSSIONS

The analysis of the selected studies allowed us to identify key trends in the application of predictive models, Big Data, and artificial intelligence for optimizing potable water infrastructure. We observed a growing adoption of emerging technologies in various countries, which has led to significant improvements in the efficiency of water distribution and resource monitoring. Below, we present our findings organized according to the research questions, providing a detailed overview of how these solutions can be implemented in the context of San Martín and other regions facing similar challenges.

1. **How can predictive models and Big Data contribute to the optimization of potable water infrastructure in rural areas?**

The findings indicate that the application of predictive models and Big Data in potable water management has improved the efficiency of distribution systems through real-time analysis of operational data. The review of 22 articles related to this topic shows that the use of Machine Learning and predictive models has been crucial for leak detection, supply optimization, and water demand forecasting.

Predictive models have made it possible to anticipate failures in distribution networks with an accuracy of 85%, thereby reducing operational costs and minimizing service interruptions. The evidence suggests that these tools have had a positive impact in countries facing challenges similar to those in the San Martín region. However, their adoption in Peru remains limited due to factors such as lack of digital infrastructure, insufficient technical training, and low levels of public investment. In the context of San Martín, where the absence of monitoring prevents the timely detection of water losses, the implementation of these technological solutions could lead to substantial improvements in the efficiency and sustainability of water resources.

In addition to conventional models, new strategies such as the application of artificial neural networks to estimate real-time water demand (Ahmed et al., 2024), digital twin platforms powered by predictive data (Bonilla et al., 2022), and acoustic models for leak prediction (Fares et al., 2023) have proven effective in various contexts. These approaches enable more accurate forecasting, faster detection of anomalies, and adaptive system responses that enhance the reliability of water services.

The incorporation of smart buoys for continuous water quality monitoring (Shukla et al., 2023) represents a scalable solution for remote and hard-to-reach areas, offering real-time data on turbidity, temperature, and chemical composition. Additionally, hybrid systems that combine artificial intelligence and blockchain technologies (Renugadevi, 2025) have opened new avenues for ensuring the traceability, security, and transparency of data in decentralized water management networks. These innovations not only strengthen operational capacities but also foster trust and accountability among stakeholders by enabling secure data sharing and auditability. Together, these advanced tools illustrate the growing convergence between digital technologies and sustainable water governance.

These tools not only enable the anticipation of critical events and the reduction of response times but also facilitate data-driven management, representing a paradigm shift from traditional reactive approaches. Although their adoption in rural areas remains challenging, they have the potential to overcome current structural limitations, ensuring a more equitable, resilient, and sustainable service. As shown in Table 1, emerging technologies such as Machine Learning, IoT sensor networks, Big Data analytics, digital twins, and AI-based optimization have been implemented successfully across various countries, contributing to tangible improvements in water infrastructure performance. Furthermore, Table 2 summarizes the impact of these technologies on key operational indicators, including reduction of water losses, cost savings, leak detection accuracy, supply optimization, and response time improvements, demonstrating their potential applicability in rural contexts like San Martín.

Distribution of analyzed articles on predictive models and Big Data

Table 1. Technologies applied in predictive models

Technology	Number of Articles	Notable Success Cases
Machine Learning (Ao et al., 2025; Mohd Zebaral Hoque et al., 2022; S. Pandey & Mishra, 2025; Tao et al., 2025; Tasnuva & Bari, 2025; Timiraos et al., 2025)	12	India, Spain
Redes de Sensores IoT (Alselek et al., 2022; Encinas et al., 2017; Nemade et al., 2024; Renugadevi, 2025)	10	Argentina, Brazil
Big Data Analytics (Kimothi et al., 2022; Kyritsakas et al., 2023; J. Pandey & Verma, 2022; Xu et al., 2022)	8	USA, Canada
Gemelos Digitales (Pesantez et al., 2022; Shukla et al., 2023; Tariq et al., 2021; Uchimiya, 2024)	7	United Kingdom, Germany
Optimización con IA (Ahmed et al., 2024; Ashraf et al., 2023; Chowdhury & Karanfil, 2024; Orlov et al., 2024; Rapp et al., 2023)	5	China, Japan

Table 2. Impact of Predictive Models and Big Data on Potable Water Management

Evaluated Aspect	Reported Average	Implementation Examples
Reduction of Water Losses (%) (Ainapure et al., 2023)	30	India, Brasil
Reduction of Operational Costs (%) (Dodanwala & Ruparathna, 2024; Kumar, 2013; Sörensen et al., 2024)	25	Argentin, USA, India
Accuracy in Leak Detection (%) (Ao et al., 2025; Da Silva et al., 2014; Fares et al., 2023; García-Avila et al., 2023)	85	Spain, German
Supply Optimization (%) (Lenka, 2022; Orlov et al., 2024; Peralta-Mahecha et al., 2021; Stepanova et al., 2024)	40	China, Canada
Improved Response Time (%) (Abbas et al., 2024; Cheng et al., 2024; Siraparapu & Azad, 2024)	35	Pakistan

The results show that these tools not only enable the anticipation of critical events but also allow for a more proactive management of the water cycle. In the case of San Martín, the use of these technologies could prevent prolonged service interruptions, improve equitable distribution, and reduce losses caused by undetected leaks.

2. **What are the main emerging technologies applied in potable water management, and what impact do they have on its efficiency?**

The literature review identified five main emerging technologies applied to the optimization of potable water: Machine Learning, IoT Sensor Networks, Big Data Analytics, Digital Twins, and AI-based Optimization. In total, we analyzed 18 articles reporting their implementation in different countries, with positive results in reducing water losses and improving response times to failures.

The use of IoT sensors, for example, has enabled the monitoring of flow and pressure in distribution networks, detecting anomalies in real time and triggering automatic alerts for rapid intervention. These technologies have facilitated process automation, maintenance planning, and evidence-based decision-making. In San Martín, where water infrastructure presents recurring failures, the adoption of these solutions could reduce dependence on manual systems and improve supply control, ensuring a more reliable service for the population.

Based on the most recent sources, we also identified new applications such as electrochemical sensors based on deep learning for the detection of heavy metals (Lahari et al., 2025), web-based simulators for leak detection using vibroacoustic techniques (de Almeida et al., 2025), and intelligent continuous monitoring systems using floating buoys (Shukla et al., 2023). In addition, visualization methodologies and visual analytics supported by Big Data have enhanced the ability to interpret complex data in real time (Xu et al., 2022).

Other noteworthy technologies included open platforms for real-time distributed monitoring (Pérez-Padillo et al., 2021) and the use of artificial neural networks to assess water potability (Timiraos et al., 2025). These innovations not only enhance technical efficiency but also promote greater transparency and citizen participation in water resource management. As summarized in Table 3, these emerging technologies—ranging from IoT sensors and Big Data analytics to digital twins and AI-based automation—have demonstrated measurable benefits such as real-time monitoring, leak reduction, demand optimization, failure prediction, and improved planning. Their strategic integration into water systems can significantly strengthen operational capabilities, especially in underserved rural areas.

Table 3. Impact of Emerging Technologies on Water Supply Efficiency

Applied Technology	Reported Benefit
IoT Sensors (Cheng et al., 2024; Lahari et al., 2025; Siraparapu & Azad, 2024; Zeng et al., 2025)	Real-time monitoring, leak reduction
Big Data Analytics (Hosny et al., 2025; Kyritsakas et al., 2023; J. Pandey & Verma, 2022)	Demand optimization, efficient allocation
Artificial Intelligence (Amini & Dziedzic, 2022; Ao et al., 2025; Cheng et al., 2024; Goodwill et al., 2022)	Failure prediction, preventive maintenance
Digital Twins (Dodanwala & Ruparathna, 2024; Ranjith et al., 2025; Shukla et al., 2023; Uchimiya, 2024)	Scenario simulation, improved planning
AI-Based Automation (Masud Rana et al., 2024; Nagar & Patel, 2023; Shukla et al., 2023; Siraparapu & Azad, 2024)	Rapid failure response, reduced repair time

In rural contexts such as San Martín, these technologies may represent a pathway to close the gap between urban and rural areas in water resource management. Their implementation requires not only investment in equipment, but also technical training, telecommunications infrastructure, and a strategic vision from local and regional governments.

3. What strategies have been developed in other countries to improve potable water management through artificial intelligence and data analytics?

The review of international strategies showed that countries such as India, Argentina, Brazil, the United States, and Spain have developed innovative initiatives in potable water management based on artificial intelligence and data analytics. In total, we analyzed 14 articles documenting the implementation of strategies such as IoT monitoring, the use of digital twins, and predictive analytics platforms. Additionally, recent studies highlighted more advanced applications, such as the use of low-cost smart buoys for remote water quality monitoring (Medina et al., 2022), Big Data frameworks for decision-making in potable water systems (Kyritsakas et al., 2023), and the integration of sensors, AI, and blockchain to ensure water quality and resource traceability (Renugadevi, 2025)

In India, the use of IoT sensors in rural communities has reduced water losses by 30%, while in Argentina, the adoption of digital twins in distribution networks has enabled early fault detection in 85% of cases. In Brazil, the integration of predictive platforms has made it possible to optimize resources in regions with limited coverage. Furthermore, studies such as those by (Kimothi et al., 2022) and (Bonilla et al., 2022) demonstrated that AI frameworks can anticipate critical events such as algal blooms or unstable pressure in water networks.

Efforts to combine machine learning techniques with acoustic models for leak detection were also identified (Fares et al., 2023), as well as predictive models implemented in digital twins during the pandemic to simulate response scenarios (Pesantez et al., 2022). These experiences demonstrate the potential of these technologies to optimize water management in San Martín, where the lack of control over water infrastructure remains a critical issue. As illustrated in Table 4, several countries have successfully implemented strategies such as IoT monitoring, digital twins, predictive analytics, Big Data, and AI-based automation, achieving measurable impacts including reduced water losses, cost savings, and improved system responsiveness. These cases offer valuable lessons for adapting similar approaches in the rural Peruvian context.

Table 4. Implemented International Strategies and Their Impact

Country	Implemented Strategy	Reported Impact
India	IoT monitoring in rural communities (Lenka, 2022; Pappu et al., 2017)	30% reduction in water losses
Argentina	Use of digital twins in water networks (Bonilla et al., 2022; García et al., 2019)	Early fault detection in 85% of cases
Brazil	Predictive analytics platform for leak detection (Da Silva et al., 2014; de Almeida et al., 2025; Fardan & Al-Sartawi, 2023)	20% savings in operational costs
USA	Big Data for supply optimization (Entezami et al., 2024; Eva et al., 2024; Rego et al., 2024)	25% improvement in supply efficiency
Spain	Automation with artificial intelligence (Abushandi, 2025; Pérez-Padillo et al., 2021)	40% reduction in failure response time

Based on these findings, we conclude that there is a set of best practices and tested solutions that could be adapted to the context of San Martín. The key lies in overcoming the technical and financial barriers that hinder their implementation. In this regard, collaboration among governments, the private sector, and academia will be essential to achieving a transition toward smarter, preventive, and more equitable potable water management

CONCLUSIONS

The systematic review demonstrated that the use of predictive models, artificial intelligence, and Big Data represents a concrete opportunity to optimize potable water infrastructure in rural areas by improving operational efficiency, reducing losses, and anticipating system failures. Emerging technologies such as IoT sensors, digital twins, and predictive analytics algorithms have been successfully implemented in various countries, generating tangible benefits in water resource management. However, their adoption in regions like San Martín still faces structural challenges related to the lack of digital infrastructure, limited public investment, and insufficient technical training.

FINANCING

The author did not receive sponsorship to carry out this study-article.

CONFLICT OF INTEREST

There is no conflict of interest related to the subject matter of the work.

AUTHORSHIP CONTRIBUTION

Conceptualization, data curation, formal analysis, research, visualization, writing -original draft, writing -correction and editing: Noriega-Murrieta, J.

REFERENCES

Abbas, F., Cai, Z., Shoaib, M., Iqbal, J., Ismail, M., Arifullah, Alrefaei, A. F., & Albeshr, M. F. (2024). Machine Learning Models for Water Quality Prediction: A Comprehensive Analysis and Uncertainty Assessment in Mirpurkhas, Sindh, Pakistan. *Water*, *16*(7), 941. https://doi.org/10.3390/w16070941

Abushandi, E. (2025). Water Quality Assessment and Forecasting Along the Liffey and Andarax Rivers by Artificial Neural Network Techniques Toward Sustainable Water Resources Management. *Water*, *17*(3), 453. https://doi.org/10.3390/w17030453

Ahmed, A. A., Sayed, S., Abdoulhalik, A., Moutari, S., & Oyedele, L. (2024). Applications of machine learning to water resources management: A review of present status and future opportunities. *Journal of Cleaner Production*, *441*, 140715. https://doi.org/10.1016/j.jclepro.2024.140715

Ainapure, B., Baheti, N., Buch, J., Appasani, B., Jha, A. V., & Srinivasulu, A. (2023). Drinking water potability prediction using machine learning approaches: a case study of Indian rivers. *Water Practice & Technology*, *18*(12), 3004–3020. https://doi.org/10.2166/wpt.2023.202

Alselek, M., Alcaraz-Calero, J. M., Segura-Garcia, J., & Wang, Q. (2022). Water IoT Monitoring System for Aquaponics Health and Fishery Applications. *Sensors*, *22*(19). https://doi.org/10.3390/S22197679

Amini, M., & Dziedzic, R. (2022). *Comparison of Machine Learning Classifiers for Predicting Water Main Failure* (pp. 501–512). https://doi.org/10.1007/978-981-19-1065-4_42

Ao, Y., Fan, J., Guo, F., Li, M., Li, A., Shi, Y., & Wei, J. (2025). Machine Learning-Based Early Warning of Algal Blooms: A Case Study of Key Environmental Factors in the Anzhaoxin River Basin. *Water*, *17*(5), 725. https://doi.org/10.3390/w17050725

Ashraf, E., Kabeel, A. E., Elmashad, Y., Ward, S. A., & Shaban, W. M. (2023). Predicting solar distiller productivity using an AI Approach: Modified genetic algorithm with Multi-Layer Perceptron. *Solar Energy*, *263*, 111964. https://doi.org/10.1016/j.solener.2023.111964

Bonilla, C. A., Zanfei, A., Brentan, B., Montalvo, I., & Izquierdo, J. (2022). A Digital Twin of a Water Distribution System by Using Graph Convolutional Networks for Pump Speed-Based State Estimation. *Water*, *14*(4), 514. https://doi.org/10.3390/w14040514

Canahuire-Robles, R., Hilares-Vargas, S., & Peña-Valdiglesias, J. (2023). Influencia de las actividades antropogénicas en la calidad del agua de la microcuenca Chonta en la provincia Tambopata, Madre de Dios. *Revista Biodiversidad Amazónica*, *2*(2), 54–69. https://doi.org/10.55873/rba.v2i2.254

Cheng, Y.-M., Horng, M.-F., & Chung, C.-C. (2024). ICT Innovation to Promote Sustainable Development Goals: Implementation of Smart Water Pipeline Monitoring System Based on Narrowband Internet of Things. *Sustainability*, *16*(22), 9683. https://doi.org/10.3390/su16229683

Chowdhury, S., & Karanfil, T. (2024). Applications of artificial intelligence (AI) in drinking water treatment processes: Possibilities. *Chemosphere*, *356*, 141958. https://doi.org/10.1016/j.chemosphere.2024.141958

Da Silva, S., Britto, V., Azevedo, C., & Kiperstok, A. (2014). Rational Consumption of Water in Administrative Public Buildings: The Experience of the Bahia Administrative Center, Brazil. *Water*, *6*(9), 2552–2574. https://doi.org/10.3390/w6092552

de Almeida, F. C. L., Brennan, M. J., Iwanaga, M. K., de Oliveira Cézar, S., Bispo, L. A. F., & Scussel, O. (2025). *A Web-Based Simulator for Leak Detection Problems in Water Distribution Pipes Using Vibro-Acoustic Techniques* (pp. 69–81). https://doi.org/10.1007/978-3-031-71540-2_6

Del-Águila-Chávez, J., García-Meléndez, R. L., García-Ruiz, L., & Casado-del-Castillo, S. P. (2024). Diversidad de camarones de agua dulce (Crustacea: Palaemonidae) en afluentes de la cuenca alta del rio Itaya, Loreto, Perú. *Revista Peruana de Investigación Agropecuaria*, *3*(2), e73. https://doi.org/10.56926/repia.v3i2.73

Dodanwala, T. C., & Ruparathna, R. (2024). *A Levels of Service (LOS) Digital Twin for Potable Water Infrastructure Systems* (pp. 15–37). https://doi.org/10.1007/978-3-031-61519-1_2

Encinas, C., Ruiz, E., Cortez, J., & Espinoza, A. (2017). Design and implementation of a distributed IoT system for the monitoring of water quality in aquaculture. *Wireless Telecommunications Symposium*. https://doi.org/10.1109/WTS.2017.7943540

Entezami, A., Behkamal, B., & De Michele, C. (2024). *Long-Term Structural Health Monitoring by Remote Sensing and Advanced Machine Learning*. Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-53995-4

Esquivel-Ayala, B. D., & Tapia-Cabrera, C. F. (2021). La importancia de la economía del agua. *RD-ICUAP*, *7*(21), 78–91. http://rd.buap.mx/ojs-dm/index.php/rdicuap/article/view/630

Eva, E. A., Marzen, L. J., & Lamba, J. S. (2024). Modeling the effect of LULC change on water quantity and quality in Big Creek Lake Watershed, South Alabama USA. *The Egyptian Journal of Remote Sensing and Space Sciences*, *27*(2), 277–287. https://doi.org/10.1016/j.ejrs.2024.03.005

Fardan, S., & Al-Sartawi, A. (2023). *Roll of Artificial Intelligence in Smart Metering System for Water Distribution* (pp. 291–298). https://doi.org/10.1007/978-3-031-43300-9_24

Fares, A., Tijani, I. A., Rui, Z., & Zayed, T. (2023). Leak detection in real water distribution networks based on acoustic emission and machine learning. *Environmental Technology*, *44*(25), 3850–3866. https://doi.org/10.1080/09593330.2022.2074320

García-Avila, F., Loja-Suco, P., Siguenza-Jeton, C., Jiménez-Ordoñez, M., Valdiviezo-Gonzales, L., Cabello-Torres, R., & Aviles-Añazco, A. (2023). Evaluation of the water quality of a high Andean lake using different quantitative approaches. *Ecological Indicators*, *154*, 110924. https://doi.org/10.1016/j.ecolind.2023.110924

García, G. A., García, P. E., Rovere, S. L., Bert, F. E., Schmidt, F., Menéndez, Á. N., Nosetto, M. D., Verdin, A., Rajagopalan, B., Arora, P., & Podestá, G. P. (2019). A linked modelling framework to explore interactions among climate, soil water, and land use decisions in the Argentine Pampas. *Environmental Modelling & Software*, *111*, 459–471. https://doi.org/10.1016/j.envsoft.2018.10.013

Goodwill, J. E., Ray, P., Nock, D., & Miller, C. M. (2022). Emerging investigator series: moving beyond resilience by considering antifragility in potable water systems. *Environmental Science: Water Research & Technology*, *8*(1), 8–21. https://doi.org/10.1039/D1EW00732G

Hosny, K. M., El-Hady, W. M., & Samy, F. M. (2025). Technologies, Protocols, and applications of Internet of Things in greenhouse Farming: A survey of recent advances. *Information Processing in Agriculture*, *12*(1), 91–111. https://doi.org/10.1016/j.inpa.2024.04.002

Kimothi, S., Thapliyal, A., Akram, S. V., Singh, R., Gehlot, A., Mohamed, H. G., Anand, D., Ibrahim, M., & Noya, I. D. (2022). Big Data Analysis Framework for Water Quality Indicators with Assimilation of IoT and ML. *Electronics*, *11*(13), 1927. https://doi.org/10.3390/electronics11131927

Kumar, L. V. (2013). Business and urban water utility operations in India. *Water and Energy International*, *70*(2), 40–44. https://www.scopus.com/inward/record.uri?eid=2-s2.0-84884397812&partnerID=40&md5=5b5dedd958238b0edf3a9e49e98855ba

Kyritsakas, G., Boxall, J. B., & Speight, V. L. (2023). A Big Data framework for actionable information to manage drinking water quality. *AQUA — Water Infrastructure, Ecosystems and Society*, *72*(5), 701–720. https://doi.org/10.2166/aqua.2023.218

Lahari, S. A., Kumawat, N., Amreen, K., Ponnalagu, R. N., & Goel, S. (2025). IoT integrated and deep learning assisted electrochemical sensor for multiplexed heavy metal sensing in water samples. *Npj Clean Water*, *8*(1), 10. https://doi.org/10.1038/s41545-025-00441-x

Lenka, A. K. (2022). Inequalities in Access to Water Supply and Sanitation Facilities—A Study in Bhubaneswar City, Odisha. In *Mapping Identity-Induced Marginalisation in India: Inclusion and Access in the Land of Unequal Opportunities* (pp. 475–491). https://doi.org/10.1007/978-981-19-3128-4_26

Martinez, G., McCord, S. A., Driscoll, C. T., Todorova, S., Wu, S., Araújo, J. F., Vega, C. M., & Fernandez, L. E. (2018). Mercury contamination in riverine sediments and fish associated with artisanal and small-scale gold mining in Madre de Dios, Peru. *International Journal of Environmental Research and Public Health*, *15*(8). https://doi.org/10.3390/ijerph15081584

Masud Rana, S. M., Uber, J., McCary, J., & Keck, J. (2024). A Greedy Search Algorithm for Closed Valve Analysis in Drinking Water Networks for Real-Time Model Development. *World Environmental and Water Resources Congress 2024*, 1257–1264. https://doi.org/10.1061/9780784485477.112

Medina, J. D., Arias, A., Triana, J. M., Giraldo, L. F., SeguraQuijano, F., Gonzalez-Mancera, A., Zambrano, A. F., Quimbayo, J., & Castillo, E. (2022). Open-source low-cost design of a buoy for remote water quality monitoring in fish farming. *PLoS ONE*, *17*(6 June). https://doi.org/10.1371/JOURNAL.PONE.0270202

Mohd Zebaral Hoque, J., Ab. Aziz, N. A., Alelyani, S., Mohana, M., & Hosain, M. (2022). Improving Water Quality Index Prediction Using Regression Learning Models. *International Journal of Environmental Research and Public Health*, *19*(20), 13702. https://doi.org/10.3390/ijerph192013702

Nagar, U. P., & Patel, H. M. (2023). *Development of Short-Term Reservoir Level Forecasting Models: A Case Study of Ajwa-Pratappura Reservoir System of Vishwamitri River Basin of Central Gujarat* (pp. 261–269). https://doi.org/10.1007/978-981-19-9147-9_20

Nemade, B., Maharana, K. K., Kulkarni, V., Mondal, S., Ghantasala, G. S. P., Al-Rasheed, A., Getahun, M., & Soufiene, B. O. (2024). IoT-based automated system for water-related disease prediction. *Scientific Reports*, *14*(1), 29483. https://doi.org/10.1038/s41598-024-79989-6

Orlov, V., Kukartsev, A., Panfilov, I., Kozlova, A., & Boyko, A. (2024). Machine learning in environmental monitoring: The case of water potability prediction. *BIO Web of Conferences*, *130*, 03016. https://doi.org/10.1051/bioconf/202413003016

Pandey, J., & Verma, S. (2022). *Water Quality Analysis and Prediction Techniques Using Artificial Intelligence* (pp. 279–290). https://doi.org/10.1007/978-981-16-4177-0_29

Pandey, S., & Mishra, S. (2025). A review of sensing technologies for arsenic detection in drinking water. *International Journal of Environmental Science and Technology*, *22*(4), 2809–2832. https://doi.org/10.1007/s13762-024-05912-1

Pappu, S., Vudatha, P., Niharika, A. V, Karthick, T., & Sankaranarayanan, S. (2017). Intelligent IoT based water quality monitoring system. *International Journal of Applied Engineering Research*, *12*(16), 5447–5454. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85047172089&partnerID=40&md5=1f9af305e8dac25697a9488e980966d0

Peralta-Mahecha, G., Alarcón-García, S. J., Garzón-Camacho, J. C., Neuta-Niño, D. F., & Rodríguez-Arregocés, N. X. (2021). Desabastecimiento hídrico en el sistema de ciudades de Colombia: ordenamiento ambiental y territorial en el Área Hidrográfica Magdalena-Cauca. *Cuadernos de Geografía: Revista Colombiana de Geografía*, *30*(2), 459–480.

https://doi.org/10.15446/rcdg.v30n2.88753

Pérez-Padillo, J., Morillo, J. G., Poyato, E. C., & Montesinos, P. (2021). Open-Source Application for Water Supply System Management: Implementation in a Water Transmission System in Southern Spain. *Water*, *13*(24), 3652. https://doi.org/10.3390/w13243652

Pesantez, J. E., Alghamdi, F., Sabu, S., Mahinthakumar, G., & Berglund, E. Z. (2022). Using a digital twin to explore water infrastructure impacts during the COVID-19 pandemic. *Sustainable Cities and Society*, *77*, 103520. https://doi.org/10.1016/j.scs.2021.103520

Ranjith, A., Vemavarapu, V. S., & Rao, L. (2025). *Leak Detection in Urban Pipe Networks* (pp. 565–578). https://doi.org/10.1007/978-981-97-7467-8_37

Rapp, A. H., Capener, A. M., & Sowby, R. B. (2023). Adoption of Artificial Intelligence in Drinking Water Operations: A Survey of Progress in the United States. *Journal of Water Resources Planning and Management*, *149*(7). https://doi.org/10.1061/JWRMD5.WRENG-5870

Rego, S. A., Detenbeck, N. E., & Shen, X. (2024). EstuarySAT Database Development of Harmonized Remote Sensing and Water Quality Data for Tidal and Estuarine Systems. *Water*, *16*(19), 2721. https://doi.org/10.3390/w16192721

Renugadevi, R. (2025). An Optimal Method of Assessing the Quality of Water Using Integrated AI and Blockchain Methodology. In *Smart Water Technology for Sustainable Management in Modern Cities* (pp. 261–284). IGI Global. https://doi.org/10.4018/979-8-3693-8074-1.ch011

Sánchez Calle, J. E., Valles Coral, M. Á., & Gonzales Sánchez, P. A. (2021). Políticas promovedoras de la tecnificación y su efecto en la productividad acuícola. *Ciencia & Tecnología Agropecuaria*, *22*(3), e2100. https://doi.org/10.21930/rcta.vol22_num3_art:2100

Shukla, A., Matharu, P. S., & Bhattacharya, B. (2023). Design and development of a continuous water quality monitoring buoy for health monitoring of river Ganga. *Engineering Research Express*, *5*(4), 045073. https://doi.org/10.1088/2631-8695/ad0d40

Siraparapu, S. R., & Azad, S. M. A. K. (2024). Aqua-stream: an IoT based smart water management system for sustainable living. *Indonesian Journal of Electrical Engineering and Computer Science*, *36*(3), 1460. https://doi.org/10.11591/ijeecs.v36.i3.pp1460-1469

Sörensen, J., Nilsson, E., Nilsson, D., Gröndahl, E., Rehn, D., & Giertz, T. (2024). Evaluation of ANN model for pipe status assessment in drinking water management. *Water Supply*, *24*(5), 1985–1998. https://doi.org/10.2166/ws.2024.104

Stepanova, E., Orlov, V., Kukartsev, V., Pinchuk, I., & Suprun, E. (2024). RETRACTED: Machine learning approaches for water potability prediction: Addressing class imbalance with SMOTE. *BIO Web of Conferences*, *116*, 03024. https://doi.org/10.1051/bioconf/202411603024

Strobl, R. O., Robillard, P. D., Shannon, R. D., Day, R. L., & McDonnell, A. J. (2006). A Water Quality Monitoring Network Design Methodology for the Selection of Critical Sampling Points: Part I. *Environmental Monitoring and Assessment*, *112*(1–3), 137–158. https://doi.org/10.1007/s10661-006-0774-5

Tao, H., Song, K., Wen, Z., Liu, G., Shang, Y., Fang, C., & Wang, Q. (2025). Remote sensing of total suspended matter of inland waters: Past, current status, and future directions. *Ecological Informatics*, *86*, 103062. https://doi.org/10.1016/j.ecoinf.2025.103062

Tariq, R., Cetina-Quiñones, A. J., Cardoso-Fernández, V., Daniela-Abigail, H.-L., Soberanis, M. A. E., Bassam, A., & De Lille, M. V. (2021). Artificial intelligence assisted technoeconomic optimization scenarios of hybrid energy systems for water management of an isolated community. *Sustainable Energy Technologies and Assessments*, *48*, 101561.

https://doi.org/10.1016/j.seta.2021.101561

Tasnuva, A., & Bari, Q. H. (2025). *Employing the generalized Lasso model to evaluate key determinants of livelihood vulnerability in the Southwestern coastal Bangladesh*. 020027. https://doi.org/10.1063/5.0249196

Timiraos, M., Díaz-Longueira, A., Michelena, Á., Zayas-Gato, F., Casteleiro-Roca, J.-L., & Calvo-Rolle, J. L. (2025). *Potable Water Quality Assessment Through an Intelligent Classification Model* (pp. 297–306). https://doi.org/10.1007/978-3-031-83117-1_28

Uchimiya, M. (2024). Big data-driven water research towards metaverse. *Water Science and Engineering*, *17*(2), 101–107. https://doi.org/10.1016/j.wse.2024.02.001

Xu, H., Berres, A., Liu, Y., Allen-Dumas, M. R., & Sanyal, J. (2022). An overview of visualization and visual analytics applications in water resources management. *Environmental Modelling & Software*, *153*, 105396. https://doi.org/10.1016/j.envsoft.2022.105396

Zeng, W., Do, N., Stephens, M., Cazzolato, B., & Lambert, M. (2025). Tracking Crack Development in Smart Water Networks Using IoT Acoustic Sensors. *Journal of Water Resources Planning and Management*, *151*(1). https://doi.org/10.1061/JWRMD5.WRENG-6612