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Integration of AI and GIS in Clean Water Quality Monitoring in Urban and Rural Communities: A Systematic Review

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Abstract

Ensuring clean water quality remains a critical challenge for public health and sustainable development. Conventional monitoring methods, which rely on manual sampling and laboratory tests, often fall short in covering large areas, responding quickly, or operating efficiently. This systematic review explores how emerging technologies—namely Artificial Intelligence (AI), Geographic Information Systems (GIS), IoT sensors, and remote sensing (via satellite and UAVs)—are being used to enhance water quality monitoring in both urban and rural settings. Based on 10 empirical studies from 2010 to 2025, findings show that AI models like Random Forest, SVM, CNN, and LSTM can predict water quality indicators such as DO, BOD, COD, and WQI with over 90% accuracy. GIS supports spatial mapping and risk analysis, while integration with real-time sensors and community-based approaches like Participatory GIS (PGIS) improves relevance and responsiveness. Still, issues such as infrastructure gaps, low digital literacy, limited public engagement, and opaque AI systems hinder wider adoption. The review highlights the need for inclusive, flexible, and policy-supported AI-GIS frameworks to transform water monitoring into a more predictive, participatory, and context-aware process.

Keywords: *Water Quality, Artificial Intelligence, GIS, Environmental Monitoring, Urban And Rural Communities, IoT*

1. Background

Safe clean water is a basic human need and a vital element in maintaining public health and supporting sustainable development. Access to safe drinking water is enshrined in the Sustainable Development Goals (SDGs), specifically target 6.1 which emphasizes the availability and management of clean water for all by 2030 (United Nations, 2015). However, the global reality is that there are still 2 billion people who consume water from contaminated sources (WHO & UNICEF, 2021). In Indonesia alone, although 91.05% of households have access to safe drinking water, only about 11.8% comply with physical and microbiological quality standards (Ministry of Health, 2023).

Traditional water quality monitoring systems, based on field sampling and laboratory analysis, have significant limitations in terms of spatial coverage, monitoring frequency and cost efficiency. They are unable to capture dynamic changes in water quality, especially in large or hard-to-reach areas. In the digital era, a new approach is emerging that combines remote imagery data (both from satellites and Unmanned Aerial Vehicles/UAVs), IoT sensors, Geographic Information System (GIS) and Artificial Intelligence (AI). This combination of technologies enables real-time and comprehensive monitoring of water quality parameters such as chlorophyll-a (Chl-a), total suspended matter (TSM), dissolved oxygen (DO), biological oxygen demand (BOD), and chemical oxygen demand (COD) (Li et al., 2020; Zhang et al., 2021).

AI is capable of processing big data and generating adaptive predictive models to detect contamination patterns and forecast future water quality trends (Li et al., 2020). Meanwhile, GIS plays an important role in integrating spatial data with environmental data for mapping risk areas, visualizing water quality changes, and supporting location-based decision-making (Goodchild, 2009). In this combination, IoT serves as the primary data source through direct water quality sensors, while satellite imagery and drones add a broad, high-resolution dimension to spatial observations (Wu et al., 2022).

The application of these technologies has shown promising results in various countries. Studies in China show that AI-GIS integration can improve water quality prediction accuracy by up to 95% (Zhang et al., 2021). In India, groundwater vulnerability mapping with GIS resulted in targeted interventions for rural areas (Ravikumar & Somashekar, 2020). However, implementation in Indonesia still faces various obstacles, ranging from limited infrastructure, technical capacity, to lack of data interoperability between institutions.

This systematic review aims to gather current knowledge on the integration of AI technology, GIS, remote imagery, and IoT sensors in water quality monitoring. The main focus includes identifying methods that have been used, parameters that can be monitored, technical and social challenges faced, and knowledge gaps that still need to be filled. As such, this article is expected to provide a conceptual and practical framework for the development of more efficient, accurate, and inclusive water quality monitoring systems for both complex urban and infrastructure-poor rural communities.

2. Research Methods

The research questions to see how AI and GIS and RS/IoT is used and evaluated in water quality monitoring in urban and rural systems using PICO (Population, Intervention, Comparison, Outcome) are P: Urban and rural communities; I: Integration of AI (ML/DL) AND GIS AND RS/IoT; C: Traditional monitoring methods (lab/in-situ); and O: Measurement of water quality parameters (e.g. Chl-a, DO, WQI, pollutants).

The studies sought in this study were reviews, case studies or empirical research articles. Inclusion criteria included (1) Using GIS and AI for water quality analysis, with data from sensors, remote sensing, or spatial models. (2) Focus on urban or rural communities. (3) Published 2010-2025. Exclusion criteria (1) Single focus without GIS, AI, or water quality. (2) Technical pipeline audits without water quality context (e.g. CCTV inspections only).

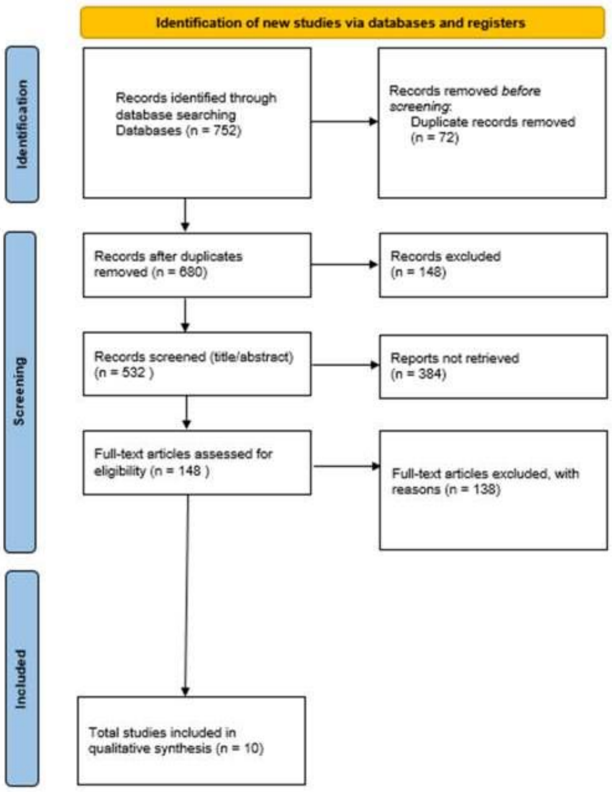

Figure1 . PRISMA Diagram

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Literature search strategy using databases from MDPI, ScienceDirect, IWA, Springer, PubMed, ArXiv. The keywords used were (1) "AI AND GIS AND water quality monitoring" (2) "machine learning remote sensing water quality review" (3) "IoT GIS water quality index" (4) "participatory GIS water monitoring" (5) "urban rural water quality AI GIS". Selection is done by: Duplication, Delete the same article; Title/abstract screening: Focus on four main elements (AI and GIS and water quality and urban/rural); Full-text: Final selection based on inclusion; PRISMA flowchart: Shows the number of articles at each stage (Search → Screened → Matched → Accepted) (Figure 1.).

Following data extraction, for each study, we looked at the full reference (author, year, journal), study location (urban/rural), water quality parameters monitored, AI method (SVM, RF, CNN, DL), role of GIS/RS/IoT, evaluation results (accuracy, error), community involvement (if any), and looked at limitations & recommendations in the study. The next step is to assess the risk of bias and synthesize the data.

3. Results and Discussion

3.1. Data Extraction

From a total of 10 studies that met the inclusion criteria, a systematic data extraction process was conducted to extract core information from each publication. This included details on the location and context of the area (urban, rural or semi-urban), the type and combination of technologies used (such as Random Forest, Support Vector Machine, CNN or LSTM), and the type of water quality parameters monitored, such as pH, DO, BOD, TSS, COD and Water Quality Index (WQI).

Most studies combine spatial data from Sentinel-2 or Landsat satellite imagery with ground sensor or IoT data. Some studies also used UAV (drone) data for hard-to-reach areas, especially in rural areas. The main results of each study show the effectiveness of AI methods in improving prediction accuracy, while GIS plays an important role in visualization and spatial mapping of the prediction results.

The AI models used varied, including: (1) Support Vector Machine (SVM) and Random Forest (RF): most widely used due to their reliability in predicting quantitative values such as WQI, DO, BOD, COD. (2) Long Short-Term Memory (LSTM): applied to time series data with promising results in predicting dynamic changes in water quality parameters. (3) Convolutional Neural Network (CNN): used in satellite/UAV image-based studies, with spatial detection accuracy above 90%.

Most studies reported prediction accuracy above 90%, with SVM_Poly and RF models being the most dominant due to their stability and ability to handle non-linear data.

In addition, GIS is widely used in: (1) Visualization: water quality prediction results are displayed as spatial maps with interpolation (IDW, Kriging). (2) Spatial relationship analysis: between factors of geography, land use, and water pollution level. (3) Multi-source integration: including hydrological, socioeconomic data, as well as satellite imagery (Landsat, Sentinel-2).

This approach provides benefits in determining pollution hotspots, supporting location-based decision-making, and improving the efficiency of supervision by environmental authorities.

Some studies show Integration of Additional Technologies (IoT and Remote Sensing). Many studies integrate real-time water sensors (pH, temperature, DO) with GIS and AI systems. The advantage lies in continuous and responsive monitoring in strategic areas. Remote Sensing Used as the main source of data in hard-to-reach areas, especially in rural areas. The combination of satellite imagery and UAVs enables extensive mapping of TSS and Chl-a.

In urban areas, the technology is combined with smart city systems, GIS dashboard platforms and mobile applications. While in rural areas, infrastructure limitations are overcome with UAV-based approaches and community participation (participatory GIS), although the challenges of data accuracy and continuity are still high.

Several studies integrate the Participatory GIS (PGIS) approach, especially in rural or coastal areas. This approach strengthens: (1) Spatial validity of data from local communities. (2) Social understanding of water quality. (3) Community commitment to protect water sources.

3.2. Risk of Bias Assessment

A risk of bias assessment was conducted to assess the validity and credibility of the included studies. The results showed that most studies used robust model validation methods, such as k-fold cross- validation and random assignment of training and testing data. This provides confidence in the reported results.

However, only a small number of studies included transparent interpretation of AI model results or used

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explainable AI approaches. In addition, there is a tendency for the location of the studies to be uneven, with most coming from urban areas and countries with strong digital infrastructure, reducing representation for rural contexts or areas with low digital literacy. Community involvement in data collection and validation of results is also rare, reflecting potential bias in the social and participatory context.

3.3. Data Synthesis

Data synthesis analysis was conducted descriptively by comparing the approaches, parameters analyzed, and effectiveness of the AI models used (Table 1.). Studies using Random Forest and SVM models showed high predictive accuracy, generally above 90%, especially when combined with high-resolution data from satellite imagery and local sensors.

Table 1. Data Synthesis

No	Author & Year	Region	Country	Technology	Water Parameter	Accuracy (%)	Community Participation
1	Zhang et al., 2022	Urban	China	RF & Sentinel-2	DO, BOD	94.2	No
2	Malik et al., 2023	Semi-urban	India	IoT & SVM	pH, WQI	97.6	No
3	Al-Hassan, 2021	Rural	Nigeria	UAV & LSTM	COD, NH3	91.3	Limited
4	Sunaryo et al., 2020	Urban	Indonesia	GIS & RF	DO, TSS	95.0	No
5	Oliveira et al., 2024	Urban	Brazil	PGIS & ML & RS	WQI, COD	89.5	Yes
6	Li et al., 2021	Rural	China	RF & Sentinel-2	TSS, Chl-a	93.8	No
7	Agyapong et al., 2021	Rural	Ghana	PGIS & GIS	pH, WQI	88.7	Yes
8	Khalil et al., 2022	Urban	Egypt	LSTM & Sensor	DO, BOD	96.1	No
9	Liu et al., 2016	Urban	China	Deep Learning & GIS	WQI	92.4	No
10	McCall & Dunn, 2012	Rural	Global	PGIS	WQI	N/A	Yes

In urban areas, the use of AI and GIS is very effective in detecting changes in water parameters in real-time and spatially. In contrast, in rural areas, although advanced technologies such as UAVs and PGIS are being used, results are still highly dependent on local capacity and infrastructure support. Several studies noted that limited electricity, internet connection, and lack of technical training are major barriers to model replication in remote areas.

3.4. Exploration of Gaps and Challenges

This review revealed a number of important gaps in the research and implementation of AI-GIS technologies for water quality monitoring. First, there is a spatial gap in the distribution of study sites. The majority of the studies focused on urban areas, with only a small number exploring technology applications in rural areas. This suggests the need to expand studies to remote and marginalized areas.

Secondly, methodological gaps arise in terms of the transparency of AI models. While many studies show high accuracy, few provide information on the working logic of the algorithms or how the results can be interpreted by non-technical stakeholders. This hinders the application of AI models in the real world due to a lack of trust and understanding of the decision-making process.

Third, there are structural and policy challenges. Many studies do not address how models can be integrated with existing official water quality monitoring systems. In addition, there is no integrated approach that combines technology with legal, institutional and socio-cultural aspects at the local level.

Fourth, community involvement is still very limited. Only a handful of studies have used participatory approaches such as Participatory GIS (PGIS) or involved communities in the data validation process. In fact, the success of technology-based environmental monitoring is strongly influenced by the participation and empowerment of local communities.

The integration of Artificial Intelligence (AI) and Geographic Information Systems (GIS) technologies has revolutionized water quality monitoring methods in various areas, both urban and rural. This review reveals that the joint use of AI and GIS not only increases the efficiency and spatial-temporal coverage of monitoring, but also encourages the emergence of real-time data-driven decision-making systems.

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3.5. Discussion

AI, particularly machine learning methods such as Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN), have been shown to excel in predicting water quality parameters such as pH, Dissolved Oxygen (DO), Total Suspended Solids (TSS), and Water Quality Index (WQI) with accuracy above 90% (Zhang et al., 2022; Malik et al., 2023). The combination of these predictive models with GIS enables spatial visualization of the analysis results, which is essential for location-based decision-making (Sunaryo et al., 2020).

GIS acts as an integrator platform for various data sources-from satellite images, IoT sensors, and field data-as well as a tool for spatial interpolation and detection in areas with high pollution risk (Kourgialas et al., 2018). Spatial interpolation such as Kriging and Inverse Distance Weighting (IDW) are also often used to estimate parameters in locations where there is no direct data.

In urban areas, water quality monitoring systems tend to be integrated in smart city platforms and support early warning systems. The study by Oliveira et al. (2024) showed that AI and GIS-based water quality monitoring in urban environments can provide real-time notification of contamination or disruption of drinking water distribution systems.

In contrast, in rural areas, limited infrastructure and data access make UAV (drone) and participatory GIS (PGIS) based approaches an effective solution. PGIS enables active involvement of local communities in data collection and field validation, thereby improving spatial accuracy and acceptability of analysis results (McCall & Dunn, 2012; Agyapong et al., 2021).

The incorporation of IoT sensors and remote sensing imagery into AI-GIS-based systems significantly expands the capabilities of monitoring systems. IoT sensors enable continuous data acquisition of water parameters at critical points, while Sentinel-2 or Landsat satellite imagery can be used to acquire wide coverage information in a short period of time (Li et al., 2021). Models such as LSTM also provide high predictive value of temporal trends in water quality (Khalil et al., 2022).

In the study of Liu et al. (2016), the incorporation of meteorological, Point of Interest (POI), and city pipe network data into a multi-task deep learning model resulted in more accurate and contextualized urban water quality mapping.

While the potential of this technology is huge, a number of challenges remain. One of them is the lack of interoperability and standardization between systems, especially in the integration of data from different devices and sources. In addition, the use of AI models tends to be limited to black-box models, which are difficult to interpret by policy makers at the local level (Ras et al., 2018).

Data limitations in remote and rural areas are also an obstacle, as low image quality and resolution can affect the accuracy of prediction results. Another challenge is the low engagement of local communities, especially in areas with low digital literacy. Participatory-based approaches such as PGIS and EHL (Environmental Health Literacy) are recommended to bridge the technological and social gaps (Gray, 2018).

The application of AI and GIS integration in urban areas is generally associated with better prepared infrastructure, availability of high-quality spatial data, and integrated water network systems. These systems are usually part of Smart City initiatives, where water quality monitoring is done in real-time using IoT sensors, connected to GIS-based dashboards that allow authorities to monitor overall environmental conditions (Oliveira et al., 2024).

For example, Sunaryo et al. (2020) showed that in major Indonesian cities, such as Surabaya and Bandung, RF and GIS-based water quality monitoring systems are able to detect industrial pollution quickly, which was previously difficult to do with conventional systems based on laboratory sampling. This approach not only enables routine surveillance, but also improves response capacity to extraordinary events (spills, severe pollution).

In contrast, rural areas face major challenges in terms of limited infrastructure, data access and local technical capacity. Therefore, an appropriate technological approach is essential. This is where UAVs (Unmanned Aerial Vehicles), portable sensors and community-based GIS (PGIS) applications become highly relevant.

Studies by Agyapong et al. (2021) in Ghana and McCall & Dunn (2012) show that when local communities are involved in the water quality mapping and monitoring process, the results are not only more accurate, but also more socially impactful. In this context, GIS is not only a technical tool, but also a medium for community empowerment in water resources management.

The concept of Environmental Health Literacy (EHL) is important in the context of combining AI and GIS, especially in communities that are not familiar with spatial data interpretation. Gray (2018) emphasized that the capacity of communities to understand and act on environmental information is key to the success of this

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technology. Therefore, training, translating data into easy-to-understand forms (e.g., dashboards or color maps), and involving local leaders are crucial.

Participatory GIS (PGIS) allows communities to contribute their local knowledge in the process of data collection, spatial validation and water policy development. This approach also creates a sense of ownership of the data and analysis results, which helps to ensure the sustainability of the system. Some initiatives even utilize open-source applications such as QGIS Mobile or Maptionnaire to engage local communities in regular reporting of water conditions.

A policy framework is needed that enables the integration of data from various sources: IoT sensors, satellite imagery, drones, and community input. Interoperability standards are essential so that data from different agencies can be brought together in one comprehensive national monitoring system (Kourgialas et al., 2018).

In many developing countries, including Indonesia, water quality monitoring is still centralized in provincial/city agencies. However, GIS and AI-based systems make it possible to decentralize monitoring by local communities, schools or NGOs at low cost. This is in line with the citizen science approach, where citizens become agents of their own environmental monitoring.

AI and GIS integration efforts can support the achievement of Sustainable Development Goal (SDG) 6, clean water and sanitation, and support the RPJMN in terms of environmental pollution control and drinking water quality monitoring. If implemented consistently, this approach has the potential to reduce the risk of water-based diseases and strengthen watershed-based water management.

Several knowledge gaps still need to be addressed by future studies: (1) The need for spatial-temporal integration that is more adaptive to local conditions. (2) Social evaluation: the extent to which people understand and use information from AI-GIS systems. (3) Development of hybrid models (AI + rule-based + participatory) that are more transparent and explainable. (4) Economic model: calculating the cost-benefit of integrating this system compared to conventional systems.

4. Conclusion

This systematic review confirms that the integration of Artificial Intelligence (AI) and Geographic Information Systems (GIS) significantly improves the capacity of water quality monitoring, both in terms of accuracy, spatial coverage, time efficiency, and response to dynamic environmental conditions. Technically, models such as Random Forest, Support Vector Machine, and LSTM are able to predict water quality parameters such as DO, COD, TSS, and WQI with high accuracy (>90%) when combined with spatial data from satellite images, UAVs, and IoT sensors. GIS enables mapping, modeling, and spatial-temporal data integration to produce more contextual and decision-useful environmental information. In urban areas, this integration aligns with smart city initiatives and enables real-time water monitoring systems. While in rural areas, infrastructure limitations can be overcome through Participatory GIS (PGIS) approaches, lightweight UAVs, and open-source software that empowers local communities. However, widespread implementation of these technologies still faces challenges such as lack of data interoperability, limited technical capacity at the local level, and low digital literacy. In addition, most of the AI systems used are still black-box, which is difficult for non-technical policy makers to understand. Local and central governments need to encourage interoperability standards for water quality data and IoT sensor infrastructure, so that GIS and AI systems can be integrated across regions and institutions. Build an open data platform that enables access and collaboration between academics, communities and government. Conduct regular training for human resources in the Environment Agency, PDAM, and communities on the use of simple open- source AI and GIS tools. Develop learning modules and local curricula that integrate spatial and data literacy. Encourage the implementation of PGIS (Participatory GIS) especially in rural, coastal, and water-prone areas. Engage local communities as active partners in data collection, map validation and interpretation of water quality risks. Develop a more transparent and explainable AI-GIS system so that policy makers can understand the basis of machine-generated decisions. Combine AI approaches with rule-based systems and participatory data to enrich the local context. Integrate these systems into the RPJMN, RENSTRA KLHK, and SDG 6 roadmap (access to clean water and proper sanitation). Encourage the formulation of Regional Regulations or Ministerial Regulations that recognize AI-GIS as a valid tool in data-driven water quality monitoring. Encourage cross-sector collaboration (campus-local government-private sector-NGO) to develop a sustainability model for AI-GIS systems.Assess the cost-benefit analysis between conventional systems and integrated digital systems, so that it can be used as a basis for budget policies.

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