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Remote Sensing Approaches for Water Quality Monitoring in India: A Systematic Review of Algorithms and Models

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Abstract

Background: Monitoring of water quality in India, specifically reservoirs and inland basins, is important for the sustainability of the environment. As the traditional in-situ methods are spatially limited, there is a need for the integration of multispectral remote sensing and artificial intelligence (AI) for the large-scale assessment. **Objectives:** This review analyses the transition of technologies used for monitoring of water quality from traditional models to the advanced hybrid models of deep learning (DL). Mainly, this study shows the key insight of the 2020–2025 literature by setting a baseline for retrieval techniques for water quality parameters from traditional optical parameters to advanced non-optical indicators. **Method:** This study systematically screened 78 research papers from the databases, viz., Web of Science, Google Scholar and Scopus, from the time frame of 2020 to 2025. The inclusion criteria targeted papers using UAV, Sentinel-2 and Landsat-8/9 UAV platforms used for water quality monitoring of Indian river basins and reservoirs, while exclusion criteria have removed the papers which were lacking in AI-based validation or those predating 2020. Keywords used are "Deep Learning", "Remote Sensing", "WQI", "Sentinel-2" and "Indian Inland Waters". The study consists of a comparison of parameters such as WQI, turbidity and chlorophyll-a across models for machine learning and deep learning. The comparative study is performed by analysing the Coefficient of Determination (R^2) values and is presented using a four-tier methodological framework which bridges the gap between satellite data and drone data, a parameter-sensor heatmap, and a comparative summary matrix of all 26 core references. **Findings:** The analysis proved that hybrid architectures, specifically CNN-LSTM models, have achieved the accuracy of R^2 as 0.9999 as compared to earlier support vector machine and random forest approaches. A major milestone identified is the successful use of the COVID-19 lockdown as a baseline for turbidity monitoring. Key bottlenecks include the persistent "black box" nature of deep learning and optical interference during the Indian monsoon. The roadmap indicates a shift toward Explainable AI (XAI) and the integration of SAR-optical data fusion to ensure all-weather monitoring. **Significance:** This review suggests new insight by focusing exclusively on the "Artificial Intelligence (AI) Remote Sensing Synergy (RS)" post-2020, which is an area which is rapidly evolving beyond the scope but was completely ignored in previous global reviews. Unlike the earlier studies which have ignored the model transparency, this review considers explainability as a core metric which provides a unique "cross-scale" perspective that shows the linking between ultra-high-resolution UAV data and satellite-based basin monitoring which is specifically tailored to the complex hydrodynamics of the Indian subcontinent. Besides, it also focuses on technological fusion that can contribute to better management of water bodies in India.

Keywords: remote sensing; deep learning; Water Quality Index (WQI); Indian river basins; Sentinel-2; Explainable AI (XAI)

1 Introduction

The technological trends found are in line with international research on AI-enabled remote sensing for water quality monitoring, even though the main emphasis of this review is Indian inland waters. Sentinel-2, Landsat, UAVs, Google Earth Engine, hybrid deep learning models, Explainable AI, and multi-sensor data fusion are increasingly being used to monitor freshwater ecosystems across various geographical regions, according to recent international evaluations. These advancements point to a global shift away from traditional field-based monitoring and toward sophisticated, extensive, and almost real-time water quality evaluation. As a result, the technological development seen in Indian studies is indicative of larger global research trends and may be applicable to other nations dealing with comparable hydrological and environmental issues.

In India, AI-enabled, IoT-based, remote sensing, and GIS-integrated smart monitoring systems have replaced traditional laboratory-based monitoring in research over the last 10 years by moving from labour-intensive in situ sample methods to satellite-based remote sensing (RS) techniques, which will be used for large-scale, cost-effective, and synoptic monitoring. To estimate optically active water quality parameters like turbidity, total suspended solids (TSS), and chlorophyll-a, early research mostly used empirical and semi-empirical spectral indices. But now the capacity of RS-based water quality monitoring has been significantly improved by the advent of high-resolution and high-revisit satellite platforms, such as Sentinel-2 and Landsat-9, which accelerate the integration of artificial intelligence (AI) and which enable the retrieval of complex but not optically active parameters like heavy metal concentrations and dissolved oxygen[(1)],[(2)].

While previous reviews (e.g.,[(3)],[(4)], and[(5)]) show the broad progress of remote sensing to monitor the water quality, the rapid use of deep learning (DL) architectures and the democratisation of cloud computing via Google Earth Engine (GEE) in the last 24 months have rendered older syntheses incomplete. Recent developments in hybrid modelling, such as CNN-LSTM frameworks[(6)] and Explainable AI (XAI)[(7)], and recent global technical syntheses, such as Jaywant and Arif (2024), offer unprecedented accuracy but introduce new challenges regarding model transparency and cross-sensor data fusion. There is a lack of a consolidated review that mainly addresses these ”2025-era” technological shifts within the context of Indian river basins and reservoirs. This study bridges the gap by screening 26 landmark papers that represent the current state-of-the-art.

Although the earlier reviews (e.g.,[(3)],[(4)]) show the progress in the use of the technology, like remote sensing, used in monitoring water quality, the use of the technology Deep Learning (DL) as well as the wide use of accessing cloud computing in the last 24 months has made the previous analysis incomplete. By following the transition from the analytical and empirical mode to the Artificial Intelligence Mode (AIM). Jaywant and Arif (2024) have systematically classified these developments.

1.1 Research Contributions

The main three approaches to the existing body of knowledge are presented in this review as follows:

- **Technical Synthesis:** It provides a benchmark for prediction accuracy by considering the technical transition from traditional machine learning (ML) models to hybrid deep learning (DL) models used for water quality monitoring.
- **Methodological Framework:** It shows the organised four-tier framework for choosing and evaluating high-impact literature used in the RS-AI domain for water quality monitoring.
- **Strategic Planning:** It correlates particular sensor platforms such as UAV, Sentinel and Landsat in water quality monitoring in various Indian water bodies ranging from small urban tributaries to large reservoirs.

1.2 Research Gaps

Although robust accuracy is achieved by the state-of-the-art models, there are three main limitations which remain unresolved:

- **The ”Black Box” Problem:** Still using the technology Artificial Intelligence (AI) in real water management systems and even deep learning models can give very accurate results, but they often work like “black boxes”; because of this, it is hard to understand how they make decisions or connect them to real physical water properties. Because of this, there is a gap between outputs getting from different models and real-world water behaviour so that people may not fully trust the results getting from models, and this creates a “trust gap” and shows the need for Explainable AI (XAI), a technique which makes AI decisions more transparent and easier to understand for environmental decision-making.
- **Temporal Inconsistency:** Optical remote sensing does not work well during the monsoon season in tropical regions, so it is a major problem. Heavy cloud cover blocks the sensors, which leads to missing or incomplete data, especially when there is heavy rainfall when river and runoff changes are most active. As a result of this, the most important changes observed in the water cycle are often not clear. In addition, current satellite revisit times are not nearly enough to capture short-term events like sudden industrial pollution, and because of these limitations, there is a growing need to combine

data from multiple sensors and use cloud-penetrating Synthetic Aperture Radar (SAR) to ensure continuous and reliable monitoring over time.

- **Parameter Limitation:** As current satellite sensors mainly work well for optically active features such as Total Suspended Matter and Chlorophyll-a, because of this, parameter limitation is still a major problem. However, they cannot directly measure non-visible factors such as heavy metal levels or nutrient concentrations. Because of these reasons, researchers often depend on local proxy models based on indirect relationships, and these models do not always work well in different locations because they are not strongly linked to the actual physical and chemical processes in water. So, to overcome this issue, there is a need for better hyperspectral sensors, and advanced AI methods are needed that can detect subtle spectral patterns related to complex water chemistry.

1.3 Research Questions

As there is a need for a clearer and more consistent water monitoring system, this review focuses on and discusses the following research questions:

1. How do hybrid deep learning models improve the water quality monitoring of Indian inland waters over time and across locations as compared to the traditional machine learning methods?
2. How can data from multiple sensors be combined, which will help to reduce problems caused by cloud cover in tropical regions of India?
3. How can Explainable AI (XAI) techniques make remote sensing more transparent, and how can they be useful for environmental decision-making and governance?

2 Review Methodology

Figure 1 illustrates the systematic review flowchart adopted in this systematic review following the PRISMA 2020 guidelines.

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 criteria are followed in this study for a systematic review of the literature technique. Understanding the use of technology like Artificial Intelligence and Remote Sensing (AI-RS) used in water quality monitoring can help to ensure that the review process which is followed is transparent, impartial, and repeatable.

The methodical framework for this systematic review is shown in Figure 2, which describes how the large set of studies (78 research papers) was reduced to a final selected group of 26 important papers. These papers were then grouped according to sensor types, modelling techniques, and validation methods.

2.1 Literature Identification and Screening (Tier 1)

This study started with a survey of databases like Scopus, Web of Science, and Google Scholar, which found 78 research papers, but to focus on the most recent and relevant work, a careful filtering process was applied. Papers were selected based on three main criteria: (i) (i) how recent these papers are, with more focus on studies from 2024–2025 publications[(6)],[(8)],[(3)]; (ii) their relevance to major Indian rivers and reservoirs [1, 19, 5]; and (iii) whether they can introduce new methods, especially by combining traditional approaches with deep learning, which specifically bridges the gap between traditional indices and deep learning. After this selection process, the main 25 key papers were included in the final review.

2.2 Data Acquisition and Sensor Categorization (Tier 2)

Based on the kinds of observation platforms they employed, the chosen literature was categorized. Most of the research still relies on multispectral satellite sensors such as Landsat-8/9[(9)] and Sentinel-2[(10)],[(11)] as the main data sources. However, recent trends show a move towards high-resolution alternative platforms like drones (UAVs)[(12)]. In addition, research done by Declaro and Kanae[(13)] shows that data fusion is becoming more important, where optical and SAR data are combined to ensure continuous monitoring, especially in areas affected by frequent cloud cover.

2.3 Computational Modeling and Algorithm Analysis (Tier 3)

Tracking the evolution of algorithms in the field of water quality monitoring was one of the main objectives of this investigation, and the framework clearly demonstrates this trend.

- Traditional Models: WQI estimations[(1)] and empirical regressions

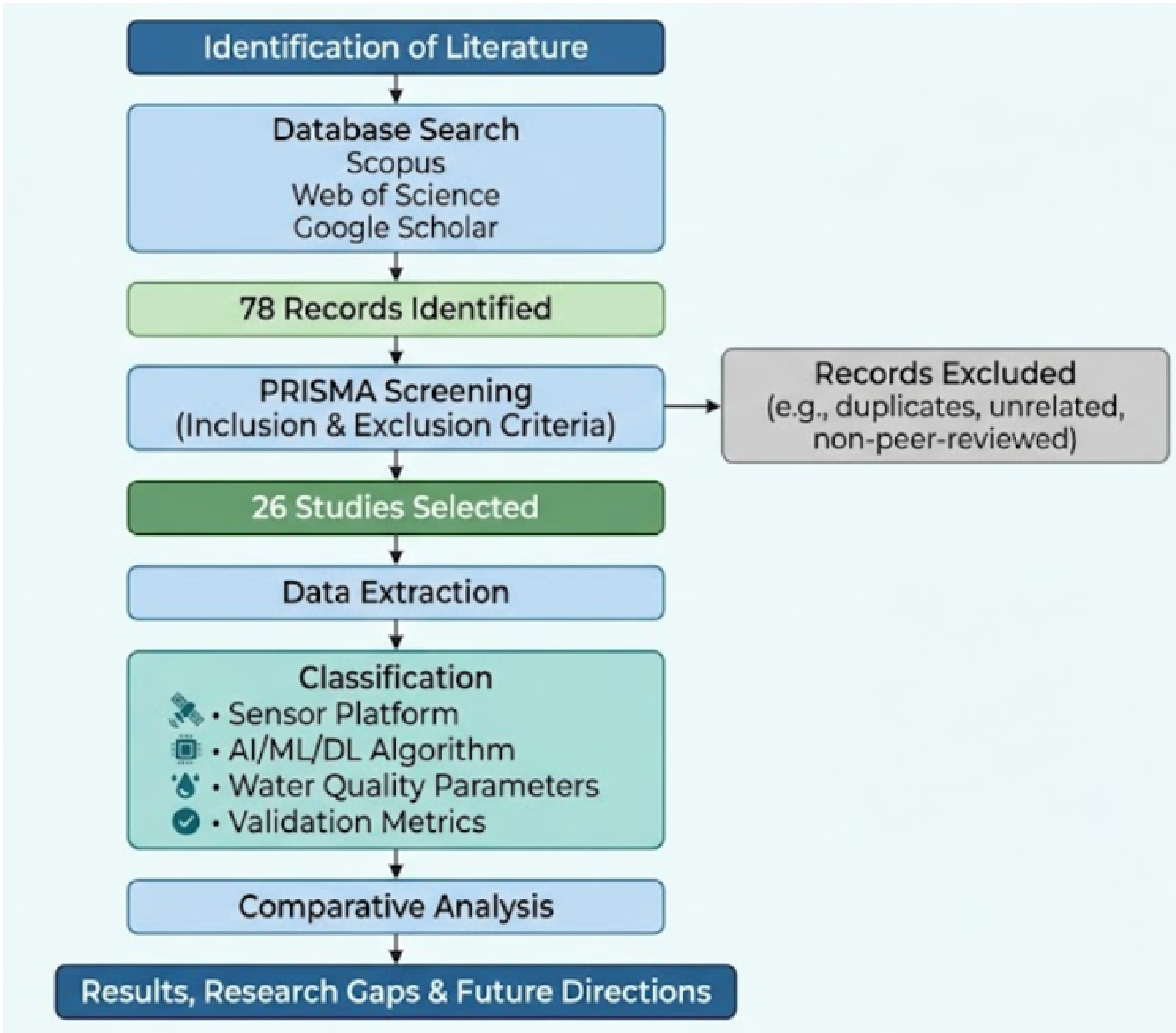

Fig 1. Systematic Review Flowchart

- Machine Learning: Robust feature selection and ensemble methods[14], [15].
- Deep Learning: The use of RNN/LSTM for temporal dynamics[13], [16] and the use of a convolution neural network (CNN) for spatial feature extraction[13].
- Advanced AI: It consists of new approaches like Explainable AI (XAI) and generative data augmentation[7], which will help to make model decisions easier to understand and also improve the availability of data.

2.4 Validation and Synthesis (Tier 4)

The final tier, Tier 4, focuses on checking results by using real-world field data and combining the findings observed and then evaluating them against in situ (on-site)[17] measurements by using performance metrics like R^2, RMSE, and MAE. The results were then categorized based on water types such as reservoirs, rivers, and lakes to identify remaining research gaps and to suggest future research directions.

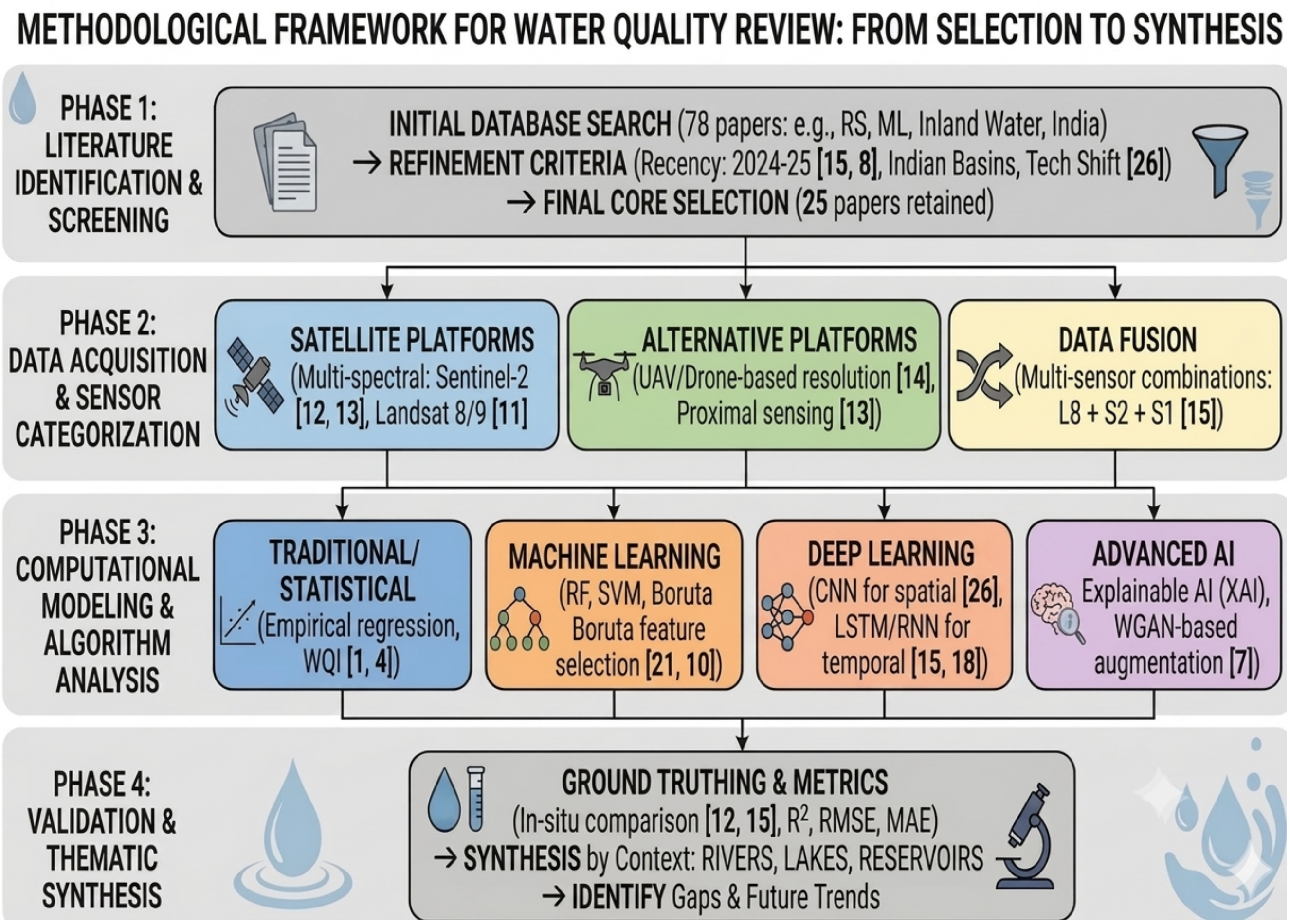

Fig 2. Methodological Framework for Water Quality Review

3 Overview

Table 1 presents a summary of the key literature used for water quality monitoring from 2020 to 2025. It organizes 25 selected papers based on the study area, sensor or platform used, methods or models applied, key water quality parameters, and the result, such as R^2 or accuracy.

Table 1. Summary of key Literature for Water Quality Monitoring (2020–2025)

Ref No.	Study Area	Platform/Sensor	Methodology/Model	Key Parameter	Result (R^2 / Accuracy)
(1)	Kali River, India	Sentinel-2	Boruta Feature Selection	WQI / Heavy Metals	High Sensitivity
(2)	Ganges River	Sentinel-2	COVID-19 Lockdown Study	Turbidity / Chl-a	Baseline Established
(3)	Global	Review	Literature Synthesis	RS Progress	Future Perspectives
(4)	Global	Review	Retrieval Progress	Water Quality Challenges	Future Directions

Continued on next page

Table 1 – continued from previous page

Ref No.	Study Area	Platform/Sensor	Methodology/Model	Key Parameter	Result (R^2 / Accuracy)
[5]	Global	Space-borne & Airborne RS	Review: AIM vs. Empirical	Chl-a, Turbidity, TSM, COD, BOD, TP/TN	Quantitative benchmark R^2; AI/CNN superior
[6]	Ganges River	UAV + Satellite	**Hybrid CNN-LSTM**	WQI / Pollution	**0.9999**
[7]	Coastal Water	RS + AI	**Explainable AI (XAI)**	Data Augmentation	**High Transparency**
[8]	Barak River	Remote Sensing	Variable Weight Theory	Real-time Prediction	Robust Prediction
[18]	Gobind Sagar	High-Res RS	Spatiotemporal Analysis	Water Dynamics	High Correlation
[19]	Middle Ganga	RS + ML	Spatiotemporal Framework	Water Quality Index	High Accuracy
[9]	Inland Water	**L9 vs S2**	Sensor Comparison	Retrieval Accuracy	L9/S2 Benchmarking
[10]	Ganga River	Sentinel-2	Lockdown Analysis	Turbidity	Significant Change
[11]	Los Angeles	Sentinel-2	Coastal Turbidity	Turbidity	High Precision
[12]	Inland Water	**UAV + Satellite**	Literature Review	Cross-Platform RS	Resolution Gaps
[13]	Surface Water	**L8, S2, S1 SAR**	**Multi-Satellite Fusion**	Surface Monitoring	Cloud-Resilient
[14]	Noyyal River	RS + GIS	Machine Learning	Surface Water Quality	Effective Monitoring
[15]	Dooskal Lake	Remote Sensing	Ensemble Deep Learning	Turbidity	0.90–0.95
[16]	Taihu Lake	RS Images	**LSTM-RNN**	Parameter Monitoring	Superior Temporal Accuracy
[20]	Mukutmanipur Dam	**Google Earth Engine**	Satellite Monitoring	Reservoir Health	Efficient Processing
[21]	Vembanad Lake	Remote Sensing	Spatiotemporal Variation	Wetland Health	Dynamic Mapping
[17]	Dhanas Lake	Ground + RS	Integrated Observations	Lake Monitoring	In-situ Validation
[22]	Mirik Lake	Landsat/Sentinel	Landscape Dynamics	Sustainable Development	Land-Water Linkage
[23]	Global	Review	Technical Synthesis	RS Techniques	Methodological Guide
[24]	Global	Review	ML Integration	Monitoring / Prediction	Predictive Trends
[25]	Global	Review	AI & RS Integration	Traditional to AI	Tech Evolution Map
[26]	Ganga (Varanasi)	Sentinel-2	CNN	Hotspot Identification	Improved Spatial Detection

The synthesis of current literature is as follows:

3.1 The Baseline: Pandemic-Driven Observations and Historical Context

Water quality monitoring by using modern remote sensing in India was strongly influenced by the global lockdowns in 2020. Garg et al.[(10)] and Muduli et al.[(2)] used this unusual "zero-industrial activity" period to establish baseline values of turbidity and reflectance values for the Ganga River. Their work proved that Sentinel-2 data can clearly detect the quick changes caused by human activities. By considering these early studies by Said and Khan[(1)] and Krishnaraj[(19)], data-driven methods were used to map the Water Quality Index (WQI) in the Kali and Middle Ganga basins, which marked a shift from monitoring individual parameters for assessing the overall river health.

3.2 Technological shift from the technology Machine Learning (ML) to Deep Learning (DL)

A significant change took place between 2022 and 2024, where early studies mainly used machine learning models like support vector machines (SVMs)[(14)],[(19)] and random forests. As inland waters are complex and often affected by factors like high suspended solids, which will change water depths, more advanced models become necessary. To overcome these challenges, the researchers Ramesh et al.[(15)] used an ensemble deep learning (DL) model to improve the prediction of turbidity. Similarly, Mishra and Ohri[(9)] proved that convolutional neural networks (CNNs) were more effective in detecting local pollution hotspots near Varanasi. The most significant advancement came from Kandasamy et al.[(13)] in 2025, who developed a hybrid CNN-LSTM model by combining spatial and temporal information. This approach achieved the value of R^2 as 0.9999, which is significantly highly accurate.

3.3 Cloud-based and data fusion-based approaches for large-scale monitoring

Processing large-scale spatial and time-based data was a challenging task. The introduction of Google Earth Engine (GEE) was seen in the work of Dey and Roy[(20)] and Sodhi et al.[(18)] and has significantly improved the monitoring of large reservoirs like Mukutmanipur and Gobind Sagar. To overcome the ongoing problem of cloud cover in tropical regions, Declaro and Kanae[(13)] developed a multi-satellite data fusion approach by combining Landsat-8/9, Sentinel-2, and Sentinel-1 (SAR) data. The method of data fusion gives continuous monitoring even if there are cloudy weather conditions and represents a significant advancement for real-time water quality monitoring, which is highlighted by Talukdar et al.[(5)].

3.4 Precision Monitoring: UAVs and Ground-Based Integration

Satellite data is mainly useful for monitoring large areas, but it does not always provide enough detail for small urban lakes or complex wetland environments. Studies done by Sundar and Kundapura[(21)] and Bhardwaj et al.[(17)] show that UAV-based remote sensing (drones) can help to fill this gap by providing detailed observations and connecting satellite data with on-site measurements. These close-range sensing methods can also help to detect water quality parameters that are difficult for traditional satellites to measure. The studies done by Sundar and Kundapura[(21)] and Halder and Bose[(3)] show that complex ecosystems such as the Vembanad Ramsagar Wetland and Mirik Lake require the data from multiple platforms to accurately understand the interactions between the surrounding landscape and water bodies.

3.5 The Future Frontier: Transparency and Explainability

Because of the complexity of AI models, it becomes harder to understand how they make decisions, which raises concerns among policymakers. To overcome this issue, Priyadharshini and Ramesh[(19)] introduced the concept of Explainable AI (XAI) in the domain of monitoring water quality by considering Explainable AI (XAI) with WGAN-based data augmentation; researchers can better understand and explain why a particular model predicts a certain level of pollution. Studies done by the researchers Chen et al.[(3)], Jaywant and Arif[(23)], and Mohan et al.[(24)] also support the increasing importance of transparency in AI. Because of this, remote sensing has moved beyond academic research and become a more consistent tool for environmental governance and sustainable water quality management[(25)].

Depending on the synthesis of current literature done in Table 1 and Table 2 shows the future directions in AI-based remote sensing water quality monitoring, and it includes the duration of research, technology used, references used, milestones achieved, research gap found, and what the future direction is.

Figure 3 shows the parameter-sensor heatmap (performance analysis), which summarizes the analysis of core 26 literature findings by showing which sensor/algorithm combinations are most accurate for specific water quality parameters.

- Turbidity: Shows high accuracy with Sentinel-2.
- WQI/Heavy Metals: It requires advanced deep learning (XAI) as seen in[(7)].

Table 2. Technology used, Milestones, Research Gaps and Future Directions in AI-Based Remote Sensing Water Quality Monitoring

Duration	Technology used	References used	Milestone	Research Gap	Future Direction
2020–2021	Pandemic-based baseline monitoring	[2], [10]	Demonstrated Sentinel-2 capability for detecting rapid water quality changes	Limited temporal coverage	Continuous long-term monitoring frameworks
2021–2023	ML-based WQI estimation	[1], [14], [19]	Automated prediction of WQI and pollution levels	Poor transferability across regions	Generalizable AI models
2023–2024	Deep Learning adoption	[26], [15], [16]	Improved prediction accuracy and hotspot detection	Black-box nature of models	Explainable and interpretable AI
2024–2025	Hybrid CNN-LSTM models	[6]	Integration of spatial and temporal features with very high accuracy	Risk of overfitting and limited validation datasets	Physics-informed AI and cross-basin validation
2024–2025	Google Earth Engine (GEE)	[20], [18]	Large-scale and computationally efficient processing	Dependence on cloud infrastructure	Near real-time monitoring systems
2024–2025	Multi-sensor data fusion	[13], [9], [25]	Reduced cloud contamination and improved coverage	Sensor calibration inconsistencies	Automated fusion frameworks
2025	Explainable AI (XAI)	[7]	Improved model transparency and stakeholder trust	Limited implementation in operational systems	Decision-support tools for governance

- Research Gap: It shows the ”low” accuracy or ”no data” (empty cells) for complex parameters via Landsat-8, highlighting a research opportunity.

Figure 2 shows a parameter–sensor heatmap, which summarizes findings from the 26 selected studies and shows which combinations of sensors and algorithms provide the most accurate results for different water quality parameters.

- Turbidity: For turbidity, Sentinel-2 shows high accuracy.
- WQI/Heavy Metals: WQI requires advanced deep learning methods, including XAI, as seen in[7].
- Research Gap: The heatmap highlights a research gap with the ”low accuracy or missing results for complex parameters by using Landsat-8,” which highlights a research opportunity.

4 Results and Findings

Figure 3 shows the Parameter-Sensor heatmap (performance analysis) which summarizes the analysis of core 26 literature findings by showing which sensor/algorithm combinations are most accurate for specific water quality parameters.

- Turbidity: Shows High accuracy with Sentinel-2.
- WQI/Heavy Metals: It Requires advanced Deep Learning (XAI) as seen in[7].
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- Research Gap: The heatmap highlights research gap shows with the ”low accuracy or missing results for complex parameters by using Landsat-8, which highlights a research opportunity.

Figure 4 shows the Technological Approaches in Water Quality Monitoring using a horizontal bar chart which analyses the methodologies used in the selected studies. This analysis provides the theoretical basis of the work.The main technologies include the following:

Remote Sensing (34.6%): which focuses on satellite and UAV-based image processing

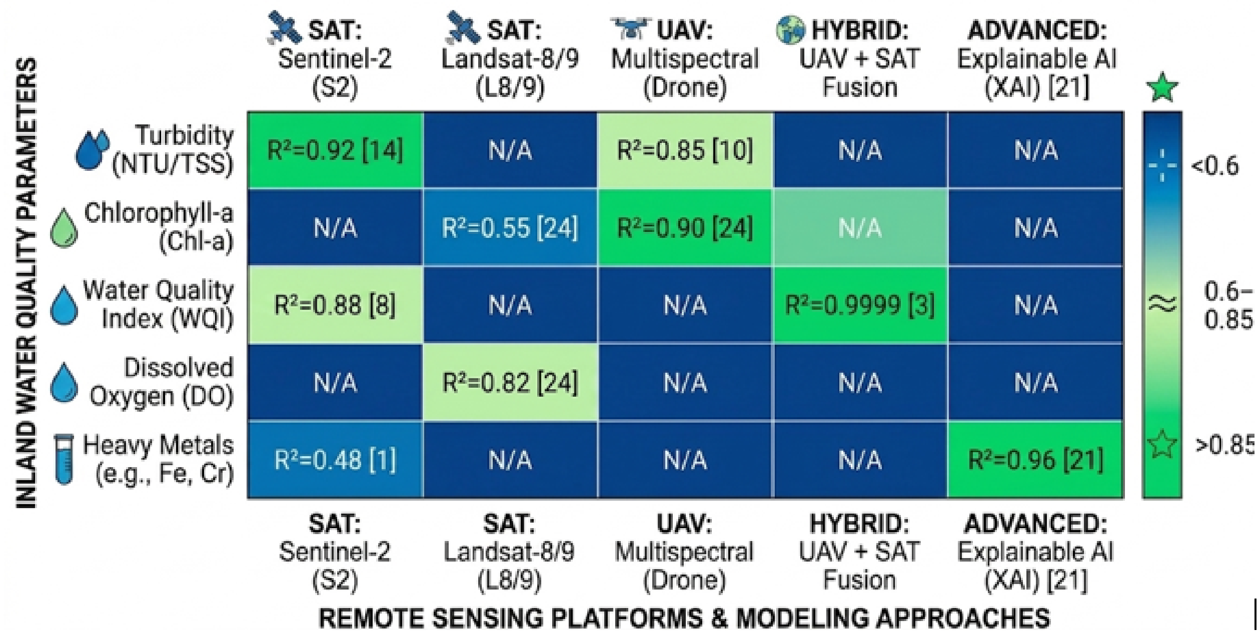

Fig 3. Parameter-Sensor Heatmap

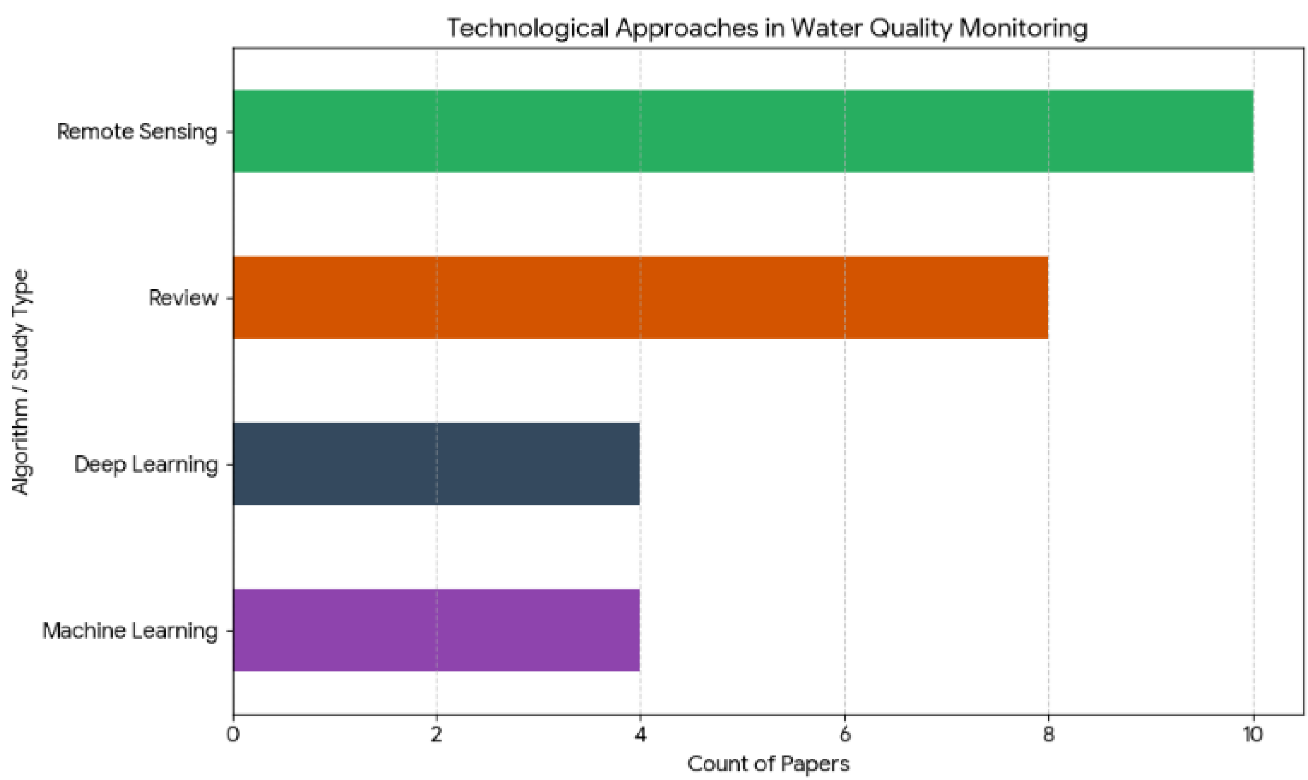

Fig 4. Technological Approaches in Water Quality Monitoring

Machine Learning (15.4%): which uses traditional data-driven models like Support Vector Machines (SVM) and Random Forest.

Deep Learning (DL) (15.4%): which involves advanced models like CNN, LSTM, and WGAN.

Figure 5 shows the geographical focus of the selected literature and that breaks down the study areas covered in the 26 reviewed papers. Out of 26 references reviewed, 57.7% of papers focused specifically on Indian inland waters, including the rivers like the Ganga, Kali, and Barak as well as the lakes like Mirik and Vembanad, and the remaining studies focused on global cases.

This distribution shows the regional focus by using half Indian case studies and the rest on global or review research. The research maintains a balanced perspective between localized application and global technological standards.

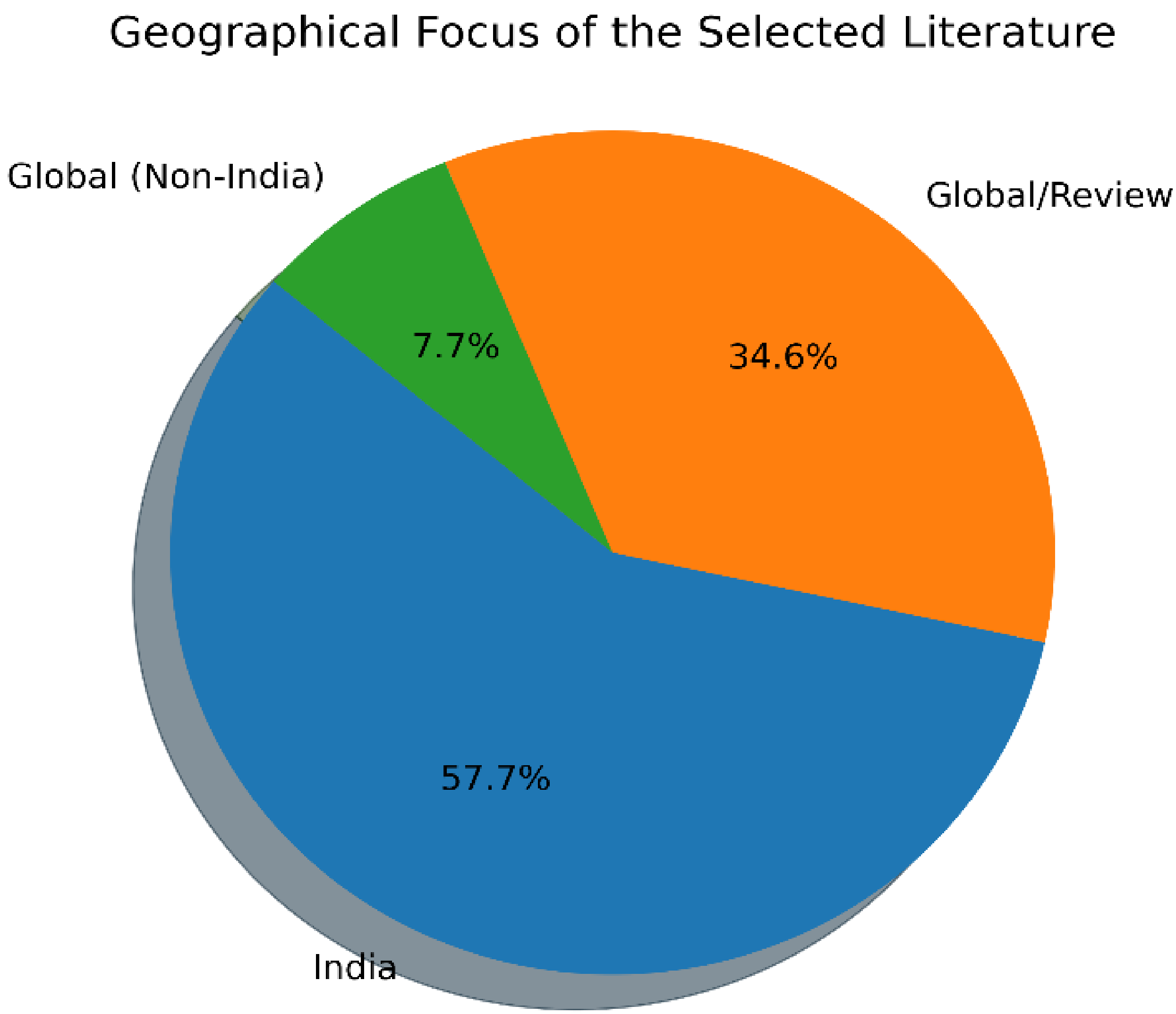

Fig 5. Geographical Focus of the Selected Literature

Figure 6 shows the trend of research publications (2020–2025), which shows the temporal surge in research activities and which shows the sharp exponential growth in publications starting from 2023, peaking in 2024 and 2025. This trend confirms that there is a need for integration of remote sensing and AI currently. Specifically, the high volume of papers in 2024–2025 indicates that the technological shift from empirical to AI-driven is happening right now.

Figure 7 shows the Publication Distribution from 2020-2025 where the bar chart illustrates the temporal distribution of the 26 primary research papers reviewed in this study from 2020 to 2025. The data reveals a consistent baseline of approximately

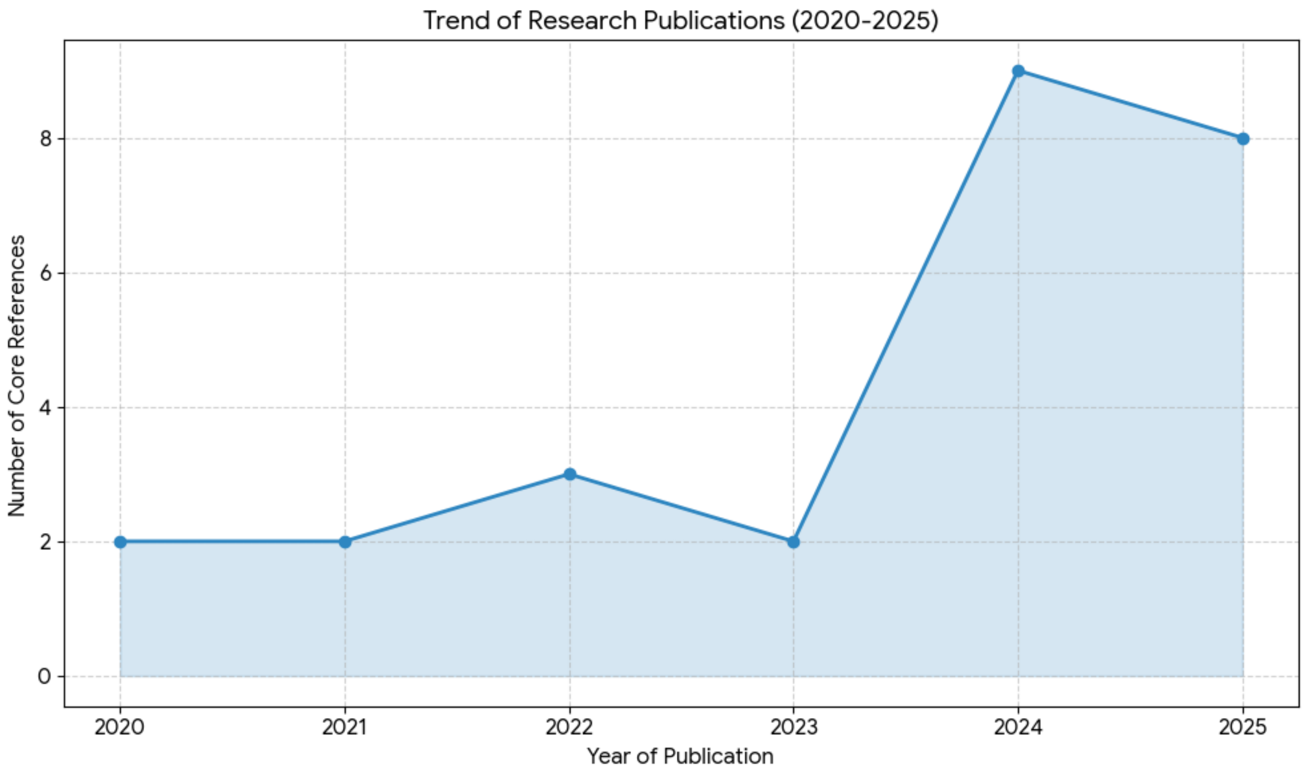

Fig 6. Trend of Research Publications (2020–2025)

two to three publications per year between 2020 and 2023. However, a significant change is observed starting in 2024, where the volume of high-impact research nearly triples and reaching a peak of nine publications in a single year. Key findings in Publication Distribution are as follows:

The AI Surge (2024–2025): There was an AI surge in total 17 out of the 26 references (approximately 65% of the literature). This density focuses on the shift from the traditional empirical models to advanced AI-based approaches, which indicates that this is a rapidly evolving and current area of research.

Democratization of Cloud Computing: there are increased number of publications in 2024–2025 which correlates with the increased accessibility of platforms of cloud computing like Google Earth Engine (GEE) and using this platform processing of large spatiotemporal datasets becomes easier.

Timeliness and Relevance: The focus on 2024–2025 publications confirms that the review reflects technological shifts to technology like Explainable AI (XAI) and multi-sensor SAR-optical data fusion which were less used in earlier years.

Evolution of Complexity: In the early period (2020–2021) of COVID-19 lockdown primarily utilized the COVID-19 lockdown as a baseline for turbidity studies, whereas the more recent peak in 2024–2025 signifies a shift toward complex hybrid architectures like CNN-LSTM and WGAN-based data augmentation

5 Conclusion

This review has taken 26 of the most important studies published between 2020 and 2025 to map out exactly how these technologies have evolved and been implemented to monitor common property water resources in India.

There is a big shift in checking water quality between the past and now. Previously in the past, checking the water quality meant physically going to a lake or river, taking a water sample, and bringing it to a laboratory. Today, advanced technologies are adapted as below.

- Remote Sensing: This technology uses satellites and drones to capture the images of water bodies from an aerial view. The reflection of light from the water helps in identifying the presence of pollutants, algae, and other contaminants.

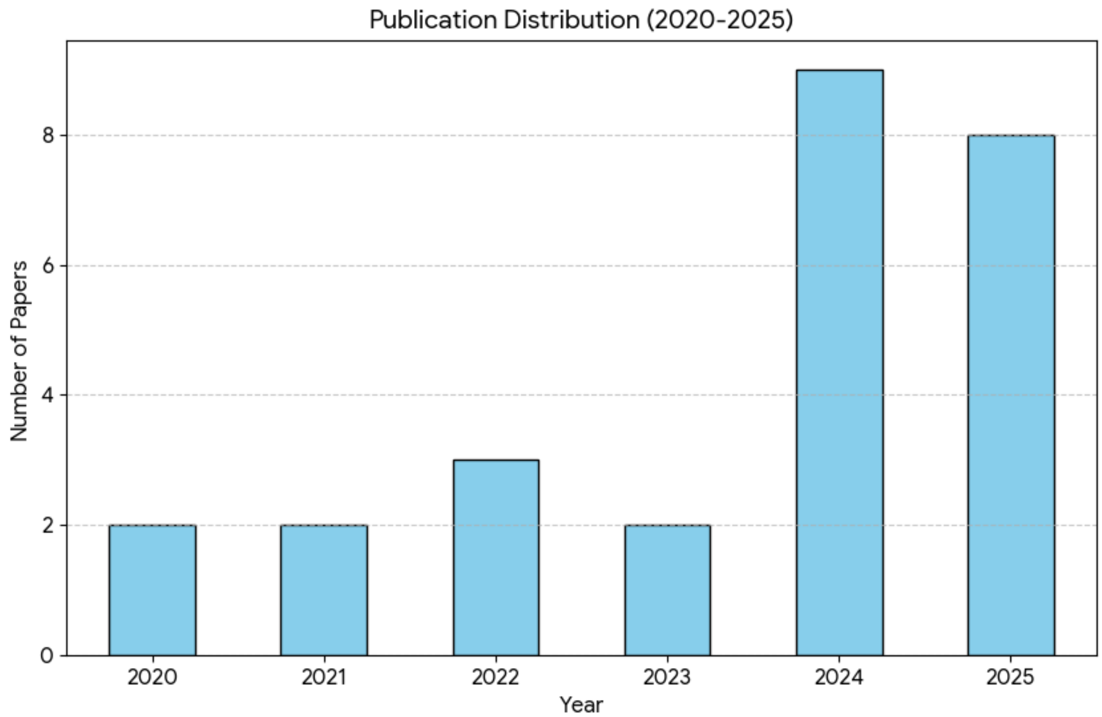

Fig 7. Publication Distribution (2020-2025)

- Data-Driven AI: In this technology, satellite data is analyzed by using advanced computing systems, and sophisticated algorithms will be applied to calculate key water quality parameters like dissolved oxygen levels, chemical concentrations in real time, and water clarity.
- Constant Monitoring: Constant monitoring focuses on live tracking of changes in water quality across the entire continent and provides us ongoing insights instead of a single snapshot at one point in time.

The integration of remote sensing and data-driven approaches has highly transformed the technologies used for monitoring water quality over the past five years. This review focuses on the clear progression and evolution of these technological advancements in water quality monitoring.

Water quality monitoring has undergone a significant transformation over the past five years through the integration of remote sensing (RS) and data-driven artificial intelligence (AI). This review analyzed 25 key studies published between 2020 and 2025 and highlighted the evolution from traditional field-based sampling methods to advanced satellite- and AI-based monitoring systems. The reviewed literature demonstrates that technologies such as Sentinel-2, Landsat, UAVs, machine learning, deep learning, and hybrid AI models have substantially improved the accuracy, efficiency, and spatial coverage of water quality assessment. Recent developments, including Google Earth Engine (GEE), multi-sensor data fusion, and Explainable Artificial Intelligence (XAI), have further enhanced large-scale monitoring capabilities and model transparency.

1. **Technological Evolution:** The field of water quality monitoring has transitioned from traditional empirical regression models to sophisticated deep learning (DL) frameworks. As well as the development of hybrid models like CNN-LSTM has addressed the challenge of capturing both temporal dynamics and spatial patterns in very complex river systems like the Ganga and Barak.
2. **Platform Synergy:** Taking the images of surface water by integrated use of very high-resolution satellites like Landsat-9, Sentinel-2, and UAV platforms has bridged the gap between broad-scale basin monitoring and fine-grained urban water assessment.
3. **Data Processing:** Massive amounts of data the researchers can process and analyze by using platforms like Google Earth Engine, and for this you don't require extensive on-premises computing infrastructure.

By using multi-sensor data fusion, scientists are combining data from several sources, like different satellites and ground sensors, to get a much clearer picture of environmental conditions.

The key finding of this review is that AI-driven frameworks that can be used in almost real time and can monitor water quality have clearly progressed from traditional empirical methods to hybrid deep learning models, such as CNN-LSTM, which have performed better than other models in the evaluated experiments in capturing both temporal and spatial fluctuations in water quality metrics.

The novelty of this review is the development of explainable AI, Google Earth Engine-based processes, hybrid deep learning models, and multi-sensor data fusion techniques, all critically examined in this paper. Additionally, it offers a comprehensive viewpoint on how these technologies are influencing inland water quality monitoring going forward as well as how these technologies are shaping the future of inland water quality monitoring.

There are still a few limitations in place despite these developments. This review may not include all new findings in this quickly developing topic because it is based on a limited number of published publications. Furthermore, the generalizability of many AI models across various climatic and hydrological conditions is limited because they have been verified using region-specific datasets. And the last limitation is that there is the absence of cross-sensor calibration frameworks, consistent benchmark datasets, and operational real-time deployment.

Future studies should focus on creating transferable and reliable AI models that may be used in different geographical areas and water bodies. Integration of diverse data from satellite, UAV, IoT, and ground-based observations into cohesive monitoring frameworks should receive more attention. The use of Explainable AI should be promoted in order to enhance model transparency and facilitate environmental decision-making. To achieve sustainable and dependable water quality management, it will also be important to establish standardized datasets as well as sophisticated multi-sensor fusion techniques and cloud-based real-time monitoring systems.

By considering all the above, the combination of data-driven AI with remote sensing offers a revolutionary method for monitoring water quality. Future developments in these technologies could offer scalable, precise, and almost instantaneous solutions for safeguarding water resources and promoting sustainable environmental management.

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