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Remote Sensing and Artificial Intelligence for River Water Quality Forecasting: A Review

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Abstract: The high population growth rate and climate change have been major problems in the proper management of water quality. Conservation of water resources and application of viable solutions are critical measures of healing degraded inland rivers. Conventional water quality monitoring and forecasting are usually labour-intensive, involving sampling and analysis procedures, which are time-consuming and costly. The introduction of real-time monitoring, remote sensing, and machine learning in the last few years has dramatically increased the accuracy and efficiency of water quality forecasting. In this paper, the approaches of machine learning are divided into three major groups, including traditional models, deep learning methods, and hybrid frameworks, as well as assessing their performance in forecasting the main water quality parameters. Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and their combination have proven to be popular in predicting water quality in inland river systems among deep learning models. The combination of real-time monitoring networks with remote sensing has greatly contributed to the data collection because it measures the spatial variability of river systems and supplements the high temporal resolution of in situ sensors. This hybrid strategy enhances the general strength and forecasting ability of deep learning models. Moreover, the input of weather forecasting data can enhance the prediction accuracy and facilitate more accurate decision-making in water resource management even further.

Keywords: Water Quality; Forecasting; Machine Learning Models; Remote Sensing; Real-Time Monitoring

1. Introduction

1.1. Background and Significance

Rivers are ecosystem and civilization lifelines and offer vital services like drinking water, agricultural irrigation, industrial supply, and habitat for aquatic life. As urbanization, industrialization, and agricultural expansion have taken their toll at a very fast rate, the quality of the river water has become a major issue in the whole world. The river systems have been degraded by pollution due to domestic sewage, industrial effluents, agricultural runoff, and climate-related effects. Such degradation of the environment is a great danger to biodiversity, human life, and sustainable development.

Monitoring and forecasting of river water quality is very important in the prevention and mitigation of water pollution. Conventional methods of water quality surveillance that rely on in situ manual water sampling and laboratory analysis are slow, resource-demanding, and spatially constrained. These restrictions require the implementation of innovative technological applications that provide real-time, mass, and economical monitoring. In this regard, remote sensing and artificial intelligence (AI) are the potential technologies that can transform the practice of water quality assessment and management.

1.2. Role of Remote Sensing in Water Quality Monitoring

Remote sensing is the process of obtaining data concerning an object or a phenomenon without any physical contact, usually using satellite images, aerial photography, or unmanned aerial vehicles (UAVs). Under water quality monitoring, remote sensing can be used to gather spatial and temporal information of different water parameters like turbidity, chlorophyll-a concentration, suspended solids, temperature, and algal blooms. This information is gathered on large geographical areas and on different time scales, which gives a complete picture of the river's health.

Some of the benefits of remote sensing are that the technique identifies patterns and anomalies over time, it can cover areas that are inaccessible or hazardous, and it can be combined with Geographic Information Systems (GIS) to conduct spatial analysis. Also, other satellite missions like Landsat, MODIS, Sentinel-2, and Aqua have increased the availability and reliability of remote sensing data to monitor environmental variables. Such technologies provide environmental scientists and policy-makers with the means of locating hotspots and tracing seasonal patterns of pollution, as well as assessing the success of pollution control efforts.

1.3. Role of Artificial Intelligence in Forecasting Water Quality

Artificial Intelligence (AI) refers to a whole group of computational methods, such as machine learning (ML), deep learning (DL), and expert systems that are used to emulate human intelligence. AI can analyze large data, learn through patterns, and make predictions with minimum human input. Applied to the forecasting of water quality, AI models are capable of analyzing remote sensing data, sensor readings, as well as past water quality data to make high-accuracy predictions of the future state of the water.

Examples of AI algorithms are Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests, Decision Trees, k-Nearest Neighbors (k-NN), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs). These algorithms are useful to predict the water quality indices, pollution source identification, and the development of decision support systems. AI can also be used to identify the hidden patterns, nonlinear correlations, and relationships among different parameters of water quality that cannot be captured in a traditional statistical model.

1.4. Integration of Remote Sensing and AI: A Paradigm Shift

The combination of remote sensing and AI is a paradigm shift in the prediction of river water quality. Remote sensing offers the needed spatial and spectral information, whereas AI will allow smart processing and forecasting. This synergy enables the creation of automated systems that are capable of offering near real-time insights, better response times, and environmental management strategies.

Integrating the spatial information in satellite images with the AI-based predictive models, the researchers will be able to create dynamic maps of the water quality conditions, predict the occurrence of pollution events earlier, and develop effective plans of intervention. This combined method is especially useful in areas that do not have the infrastructure to monitor ground-based monitoring, providing cheap and expandable solutions to water quality management.

1.5. Scope and Objectives of the Review

This review aims to critically discuss the existing condition of research on the use of remote sensing and AI methods in the forecasting of river water quality. The purpose of the paper is:

1. Emphasize the role of river water quality monitoring with regard to environmental sustainability.
2. Research different technologies of remote sensing and their use in sensing water quality parameters.
3. Examine how AI algorithms can be used to predict water quality based on various data sources.
4. Browse available literature involving the combination of remote sensing and AI in monitoring rivers.
5. Determine gaps in the existing research and propose future research lines in enhanced forecasting systems.

The review is a part of an emerging interdisciplinary research that is promoting the use of technological advancements in environmental monitoring. The paper will synthesize knowledge from various studies and give a guide to other researchers, environmental engineers, and policy-makers who aim to improve the water quality forecasting systems in rivers.

2. Literature Review

There has been a major advancement in remote sensing technologies that allow the water bodies to be monitored at a large scale in a non-invasive way. Carried out a seminal review of the use of satellite data, including MODIS, Landsat, and Sentinel, to monitor parameters like turbidity and chlorophyll-a in rivers through the use of reflectance indices [1]. In the same manner, Chawla and Mehta have pointed out the usefulness of spatially continuous sensor data such as MERIS in identifying seasonal changes and trends in water quality [2]. These studies highlighted the importance of sensors in gathering long-term environmental data that is vital in comprehending hydrological trends.

The use of machine learning (ML) algorithms in modelling nonlinear relationships between different water quality indicators has been demonstrated to be effective applied Support Vector Machines (SVM) and Artificial Neural Networks (ANN) to field data in Indian rivers, with better prediction accuracy of Biological Oxygen Demand (BOD) and pH levels [3]. Similarly, a hybrid SVM model using satellite-based indices has demonstrated more than 85 percent accuracy in the identification of river pollution zones [4]. The models work at low levels of pre-processing and adjust to changing environmental conditions.

The usage of deep learning (DL) methods is on the rise because of their capacity to learn high-level features in large, complicated data. The approach that Nguyen et al. (2021) suggested was a Convolutional Neural Network (CNN) based on Landsat images to forecast Dissolved Oxygen (DO) and turbidity at high spatial resolution [5]. In a different work, Sharma and Goyal used a Long Short-Term Memory (LSTM) network to process time-series water quality data and managed to discover temporal dependence in Ganga River measurements [6]. Such works indicate that DL models can handle both time and space in predicting the water quality.

2.1. Integration of Remote Sensing and AI for Real-time Monitoring

In the recent past, concerns have been placed on the integration of real-time sensor networks with AI to deliver instant feedback systems. Presented a cloud-based IoT-AI platform that gathered remote sensing and field data to deliver real-time water quality alerts [7]. The authors of the study by Singh and Patel employed random forest algorithms trained with MODIS images to automate the process of monitoring turbidity and suspended solids in Indian rivers [8]. The integrations make water management systems responsive and minimize labor.

The satellites cover a wide area, but Unmanned Aerial Vehicles (UAVs) or drones possess a higher resolution and are more flexible. UAV images and CNNs to identify pollutants in the local river sections with sub-meter visual resolution [9]. In a similar way possibility of using hyperspectral drone images to identify surface algae and oil spills through AI classifiers [10]. Such technologies are of high resolution that can closely monitor hotspots and sources of contamination.

Incorporation and spectral indices development. Several papers were devoted to the development and use of spectral indices to estimate the parameters of water quality. As an example, the Normalized Difference Turbidity Index (NDTI) and Chlorophyll Index (CI) have been popular. Das and Ramesh (2022) applied such indices in the application of AI models to detect eutrophication in lakes and related river networks [11]. Another study by Fang et al. (2020) is analogous, applied NDWI and MCI to predict nutrient concentrations in the Yangtze River using Random Forest [12]. These indices fill the gap between raw data from the satellite and the insights into the environment.

Ensemble generalization and robustness can be achieved by combining several AI models. Prasad et al. (2020) have come up with a hybrid system that integrates SVM and Decision Tree models with the help of MODIS imagery to classify river health [13]. Genetic Algorithms were applied by Wu et al. (2022) to optimize ANN parameters to predict the concentration of ammonia nitrogen in Chinese rivers [14]. These hybrid methods enable models to learn complementary features and compensate for the weaknesses of individual models.

Forecasting of composite indices such as the Water Quality Index (WQI) has become a point of interest. Halder and Saha (2019) used ensemble learning to forecast WQI using remote sensing and weather information in Bangladesh [15]. Liu et al. (2021) designed a deep learning pipeline based on CNN and LSTM to predict WQI values using Landsat images and demonstrated that the pipeline is more accurate than legacy approaches [16]. The tools present in these studies are used to determine the overall water quality instead of an individual parameter.

In spite of the progress, the existing models have shortcomings. Most ML models need considerable volumes of labeled training data, which is limited in developing areas. Amini et al. (2020) observed that remote sensing data can be distorted by spectral confusion caused by clouds and vegetation and influence the performance of the model [17]. Besides, Zhang and Zhang (2021) emphasized the problem of the lack of transferability, the inability of models trained on one river system to work well in another because of regional differences [18]. Such gaps point to the necessity of more generalized and versatile frameworks.

2.2. Future Trends and Recommendations

Future research will likely move toward real-time, automated monitoring systems powered by cloud computing, 5G networks, and emphasize the importance of multi-source data fusion—integrating in-situ, satellite, and social sensing data—for better forecasts [19]. And recommended the use of Explainable AI (XAI) to improve model transparency and stakeholder trust in water management decisions [20]. Emphasizing interpretability and regional customization will be key in scaling up AI-remote sensing systems globally.

3. Materials and Methods

The identification of essential water quality indicators and the assessment of forecasting model performance are the most important elements in the context of an inland river water quality forecast. These indicators are usually divided into three broad categories, i.e., physical, chemical, and biological parameters. In this review, the most frequently applied measures of performance are also highlighted as important measures to determine the accuracy and reliability of predictive models. In order to provide a thorough and current analysis, the literature used in this review is mostly comprised of the works published in the period between 2000 and 2025, which include the latest developments in the area. Also, seminal and influential works published before 2000 and the most influential works of the period 2000-2020 have been included to give a historical background and add to the knowledge of the development of forecasting methods. As the technologies of machine learning are developing, these models have found their application in most fields, such as predicting water quality in rivers.

A thorough literature search was done on Google Scholar to find relevant studies published till the year 2025. Figure 1 shows the search process. A mix of precise keywords was applied to cover the subject matter in detail, and they included: "real-time monitoring water quality," "inland river water quality forecasting," "water management," "inland river water quality deep learning," "water quality hybrid machine learning," "water quality machine learning," "water quality urbanization agriculture," and "water quality remote sensing." These keywords were carefully chosen in the sense that they cover both technological and environmental dimensions of inland river water quality prediction.

Figure 1. Overview of Review Process. The following flowchart shows the conceptual method employed in the selection of literature in this narrative review. The numerical values are approximate and are used to explain the process of review, but not a formal systematic review.

Besides the literature that is specifically dedicated to the use of machine learning methods in inland river water quality forecasting, additional sources were included when preparing the manuscript. The other sources gave important background information such as water quality indicators, sources of pollution, hydrological processes, and remote sensing techniques. As a result, the synthesis at the end of the paper incorporates the latest developments and the basic knowledge needed to gain an in-depth insight into the topic.

3.1. Hydrology Background

Observation of the quality of river water is significant in the efficient management of water and the safeguarding of fresh water. Prediction of water quality also gives advanced notifications of possible pollution incidents, and early interventions can be made. The pollution risks are susceptible to dynamic forecasting models, and this provides useful information on environmental planning and decision making.

Water management has become a very urgent issue because of the rising human demands, which include a high rate of urbanization, industrialization, and the overall implications of climate change. Water used in drinking and sanitation is not the only source of water needed, since it is also important in agriculture, energy, and industry. The necessity to manage the water resources more efficiently and in an integrated manner is even more significant as the demand on the sectors increases.

Figure 2 is a conceptual diagram that demonstrates the key drivers of inland river water quality. There are three main drivers, including weather, urbanization, and agriculture, which are fundamental in the dynamics of river systems. The first part of the diagram (A) indicates the influence of the precipitation patterns on the water quality by causing the runoff, which may cause eutrophication and raise the amount of dissolved and suspended solids in the rivers. These effects are exacerbated by human activities that change nutrient inputs and hydrological balance.

The second part (B) highlights the importance of urbanization, which leads to degradation of water due to water discharge of domestic sewage and industrial wastes. Section three (C) deals with the effects of agriculture, in which the use of fertilizers and farm animal activities deposit nutrients and organic matter in water channels by runoffs. Although climatic factors are not portrayed in Figure 2, it is one of the most important features of river quality. Other factors that may affect the composition of water and ecological balance include ice cover and road salt in winter.

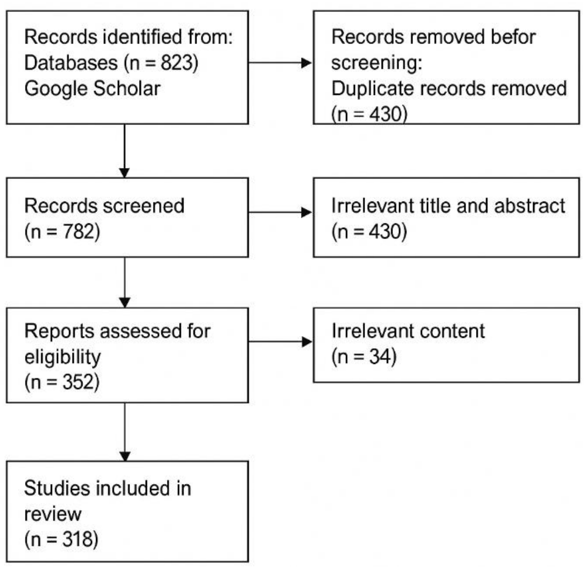

Figure 1. Review Process Flowchart

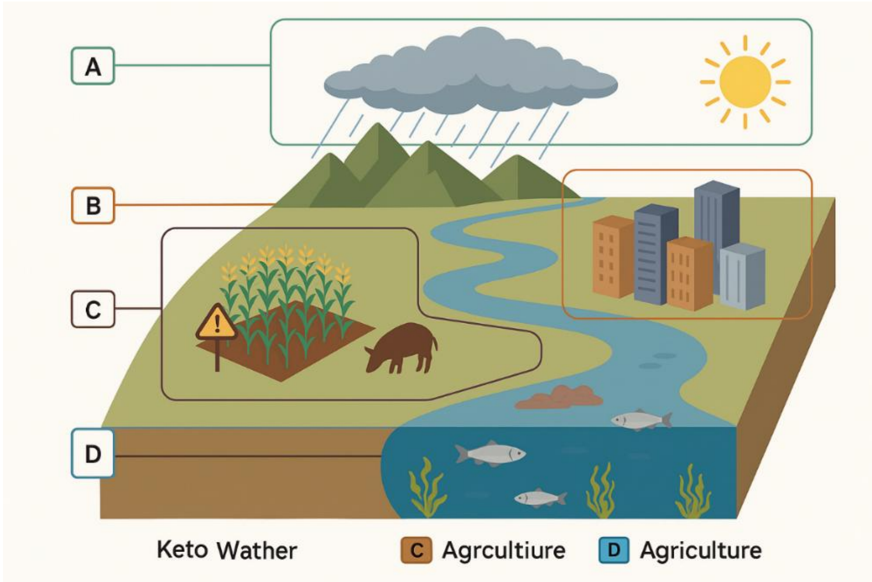

Figure 2. Theoretical scheme of River water

Figure 2. Theoretical Scheme of the River Water Quality Factors. The diagram shows the main factors that influence the quality of water in rivers, and they include the following:

Where there is seasonal ice formation, the quality of river water is significantly affected. In winter, the ice cover limits the exchange of gases between the atmosphere and the water surface, which usually results in low levels of oxygen. Ice also affects the turbidity of the water and population of algae, which are major indicators of water quality. Also, the tendency to use road salt to control the icy conditions leads to the elevation of chloride in rivers, which may affect the aquatic ecosystem. These seasonal variations show that there are complex interrelationships between climatic parameters and water quality, which further necessitate the need to come up with advanced predictive models and management strategies.

A great source of water pollution continues to be human activity. There are two broad sources of water contaminants, namely diffuse pollution and point source pollution. Surface runoff and subsurface flow of wide areas are usually the cause of diffuse pollution, whereas point source pollution occurs due to a known point of pollution, like that of industrial outflow or wastewater. Knowledge and mitigation of both types of pollution are important to ensure healthy river ecosystems.

The process of seasonal ice formation in the north also contributes greatly to influencing the quality of water in rivers. This is because during the winter months, the ice cover hinders the exchange of gases between the water surface and the atmosphere, which in most cases causes a reduction in the amount of oxygen. Moreover, the ice formation affects the turbidity and algae behavior, two important parameters that determine the quality of the water. The other issue in winter is the prevalence of road salt to control icy conditions, which in turn may raise the chloride levels in rivers and cause a hazard to aquatic life. These seasonal variations indicate the intricate interplay between climatic conditions and water quality, which underscores the necessity of better forecasting models and effective management practices.

The degradation of river water quality also owes a lot to human activities. There are two broad categories of pollution, i.e., diffuse pollution and point source pollution. Diffuse pollution is usually caused by surface runoff and underground flow of large areas, whereas point source pollution is caused by a definite, identifiable area, e.g., wastewater discharge. As opposed to point source pollution, diffuse pollution is harder to detect and control because it is widespread.

The dynamic interaction between groundwater and surface water is one of the factors that affect the accuracy of river water quality forecasting. As an example, fertilizers can be washed into the ground by rain and can slowly trickle down into the groundwater. When this groundwater subsequently mixes with surface water systems, it may add too many nutrients into rivers, which may cause problems such as eutrophication. The knowledge of these multifaceted interactions is paramount in coming up with viable forecasting methods and sustainability practices in water management.

3.2. Water Quality Indicators

Water quality indicators are quantifiable measures that give critical information on the physical, chemical, and biological properties of water. These are important indicators in the evaluation, monitoring, and forecasting of the condition of river ecosystems. The success of water quality forecasting greatly relies upon the proper choice and examination of these relevant indicators.

These parameters are normally classified into three categories, namely physical, chemical, and biological indicators in river water quality forecasting. Examples of physical indicators are temperature, river discharge, turbidity, total dissolved solids (TDS), and total suspended solids (TSS). These elements affect the infiltration of light, the movement of sediments, and the general water habitat. Chemical indicators tell us about the chemical content of the water and usually act as indicators of pollution or ecological stress. Typical chemical measures are dissolved oxygen (DO), biological oxygen demand (BOD), chemical oxygen demand (COD), pH, nutrients (e.g. nitrates and phosphates), and heavy metal concentrations.

Biological indicators rely on the occurrence and abundance of certain organisms that will react to alterations in the quality of water. Important biological indicators are algae and coliform bacteria that may indicate nutrient enrichment and organic waste contamination, respectively.

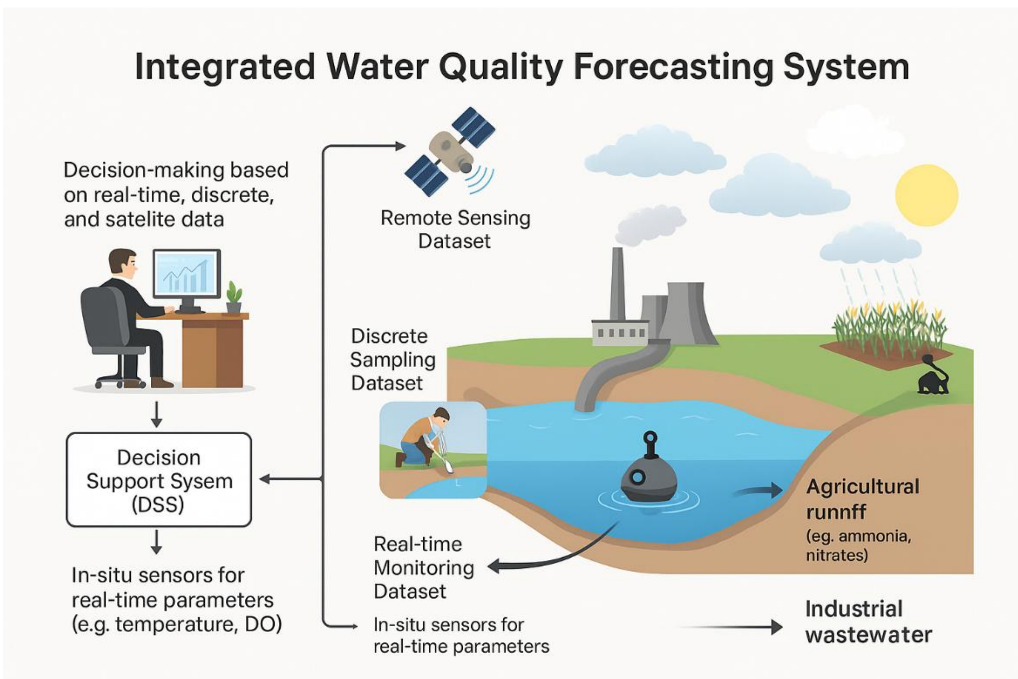

Figure 3. A Schematic diagram

The indicators of water quality are quantitative parameters, which are used to provide crucial information on the physical, chemical, and biological features of water. These indicators are important in the evaluation, monitoring, and prediction of the state of river systems. The successful forecasting of water quality relies on the wise choice and evaluation of the most applicable indicators, which are a reflection of the health of the aquatic ecosystems. Within the framework of the forecasting of water quality in rivers, these indicators are usually divided into three basic types:

Physical indicators are temperature, discharge, turbidity, total dissolved solids (TDS), and total suspended solids (TSS). Chemical indicators include dissolved oxygen (DO), biochemical oxygen demand (BOD), chemical oxygen demand (COD), pH, nutrients, and heavy metals. The main biological indicators are the occurrence and abundance of algae and coliform bacteria.

Table 1 will give a complete picture of these widely used water quality indicators, their fundamental roles, and the factors that affect them. The table represents the most common parameters that were studied, but it should be mentioned that in the future, a wider selection of indicators may be used.

New pollutants like the dissolved organic compounds, which include artificial sweeteners, iodinated contrast agents, antibiotics, and pesticides, are becoming of interest as significant water quality indicators. They are usually deposited in the river system via the wastewater discharge and surface runoff, and can be used as a good indicator of pollution and human influence in the inland river system.

Table 1. Detailed information for water quality indicators

Type	Indicator	Core Function and Impact	Key Influencing Factors
Chemical	TDS (Total Dissolved Solids)	Indicates drinking water quality and groundwater–surface water exchange. High turbidity often leads to high TDS.	Geological composition, climate, human activities
	TSS (Total Suspended Solids)	Represents suspended particle concentration; critical for aquatic health and directly linked to turbidity.	Climate, human activities
	DO (Dissolved Oxygen)	Essential for aquatic ecosystem health. Low DO (< 2 mg/L) signals hypoxia or dead zones.	Water temperature, algal blooms
	BOD (Biochemical Oxygen Demand)	Reflects the oxygen needed by aerobic microbes to decompose organic matter; indicates eutrophication.	Organic pollution, microbial activity
	COD (Chemical Oxygen Demand)	Measures total pollution (biodegradable and non-biodegradable); a faster alternative to BOD.	Industrial waste, surface runoff
	pH	Extreme pH values harm aquatic organisms and disrupt water chemistry.	Acid rain, industrial discharges, and agricultural runoff
Biological	Nutrients (TN, TP, Ammonia)	Support plant and algal growth; excess leads to eutrophication, harmful	Fertilizers, domestic sewage

	algal blooms, and oxygen depletion.	
Heavy Metals (Pb, Hg, Cd, Cr)	Even at low levels, these metals are toxic and pose serious risks to aquatic life and humans.	Industrial discharge
Algae	Algal blooms disturb ecosystem balance; some produce harmful toxins. Chlorophyll a is used to estimate algae presence.	Nutrients, temperature, and turbidity
Coliform Bacteria	Indicator of fecal contamination. High levels increase BOD and reduce DO, indicating poor water quality.	Fecal matter, agriculture, and pollution

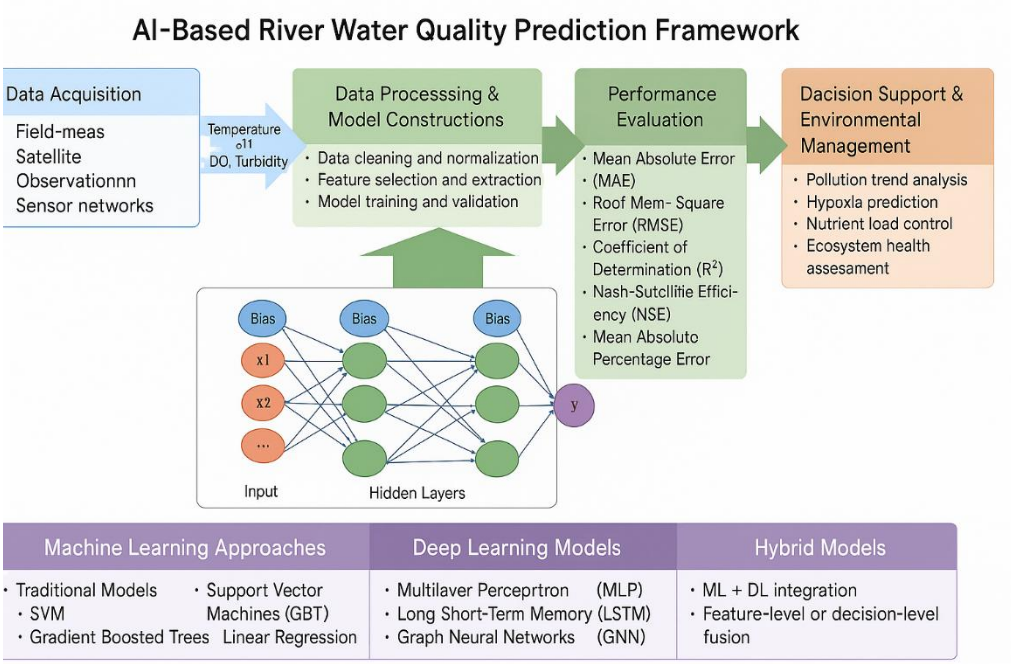

Figure 4. AI-based river framework

Besides coming up with the models, interpreting the results is an important part of water quality forecasting. It includes the employment of performance indicators, which are quantitative measures that determine the effectiveness, accuracy, and reliability of machine learning models. Such indicators assist in establishing the degree to which a model is able to predict the main parameters associated with river water quality, as shown in Figure 4. Measures like the Mean Squared Error (MSE) can be applied to measure the performance of a model, especially in cases when there are outliers. Root Mean Squared Error (RMSE) is the error expressed in units of the predicted variable, and it makes the results easier to interpret. The less sensitive to outliers, Mean Absolute Error (MAE), is a stable measure of accuracy. In the meantime, Mean Absolute Percentage Error

(MAPE) gives information about the relative predictive performance of the model. In any scenario, the lower the values of these metrics, the better the model performance, which instills more confidence in the applicability of the model in the real world.

3.3. Machine Learning Models

As a way of solving the problem of water quality forecasting in rivers, traditional machine learning (ML) methods have been used over the years because they can handle structured data, determine its underlying patterns, and generate predictive results. These models are based on manually designed features and tend to be more interpretable than deep learning methods. They have been proven to be effective, especially in cases where the size of the data is small or less complex, hence applicable in a majority of environmental monitoring activities.

Multiple linear regression is one of the most popular traditional models, and it regards river water quality forecasting as a regression issue-predicting continuous values over time. Support Vector Machines (SVMs), in turn, are applied to classification tasks and work by locating optimal hyperplanes to differentiate data points into different classes, which is why they can be applied to predicting water quality classes. Gradient Boosting Machines (GBMs) have increased in popularity; these models are an iterative approach to prediction accuracy by fitting multiple weak learners together. Among the most famous are XGBoost, LightGBM, and CatBoost that are performance-oriented and fast. Although the traditional machine learning models are less complex and easy to comprehend, they are slowly being outstripped by the newer and more adaptable models. They have shortcomings that are evident with high-dimensional or large, or highly dynamic datasets.

3.4. Deep Learning Models

Deep learning has revolutionized data-driven modeling, particularly in areas where data are non-linear, complex, and high-dimensional, e.g., the prediction of river water quality. Such models can learn complex interactions and time dependencies between many variables without requiring large amounts of manual feature engineering. Unlike the conventional methods, deep learning is superior in dealing with large-scale datasets that incorporate both space and time. This also renders it especially suitable for the modeling of dynamic and interconnected river ecosystems. The recent advances in the field of sequence modeling, best known by their capability to deal with long-range dependencies and parallel processing. The models of deep learning provide superior predictive efficiency and capacity to identify hidden relationships in huge and intricate information, and are thus gaining attention as modern water quality forecasting tools.

3.5. Constraints of Methods of Forecasting Current River Water Quality

Despite the positive outcomes of the river water quality forecasting models, they continue to be affected by a number of shortcomings. Most of these difficulties are brought about by the complexities of environmental systems and the technical limitations of modeling methods.

As much as machine learning has introduced great changes in forecasting, it is not devoid of disadvantages. Other problems like overfitting, dependence on data quality, and lack of interpretability are still significant. These shortcomings make predictions less accurate and reliable, and they present difficulties to researchers and practitioners.

3.6. Conventional Machine Learning Models

The simplicity and the ease of implementation of the traditional machine learning models make them appropriate to be applied in some forecasting tasks. But this ease of use brings in its wake its drawbacks. Such models have difficulty dealing with high-dimensional, large-scale data, particularly those with complicated temporal or spatial structures. Non-linear relationships between the indicators of water quality often make the traditional algorithms insufficient. As an example, models such as linear regression cannot depict complicated interactions, and this decreases their predictive capabilities in dynamic environmental systems.

4. Conclusion

River water quality forecasting has experienced significant developments in the past few years, with a replacement of traditional monitoring tools with more modern methods, which include remote sensing, real-time data, and machine learning. Although the traditional methods are useful in baseline monitoring, they have often become expensive, labor-intensive, and lack spatial and temporal resolution to provide timely and accurate forecasts.

Machine learning has become a revolutionary method in this area, allowing analyzing large and complex data, including non-linear patterns, and enhancing the accuracy of the prediction in both space and time. In this review, various machine learning approaches have been discussed, such as classical models, deep learning models, and hybrid methods. Deep learning models, especially Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, are among the most promising in terms of modeling spatiotemporal dynamics of river systems. These models improve predictive performance, particularly when they are used to deal with large-scale and heterogeneous data. Nevertheless, even with the benefits, issues of high computational demands, a large amount of training data, and interpretability of models continue to limit their use. In addition, the existing forecasting techniques are yet to be in a position to offer long enough, real-time forecasts to support the requirements of efficient water resource management and early warning systems. Access to the current high-resolution data set is a major obstacle to the further enhancement of the accuracy of forecasts. To conclude, machine learning has provided valuable improvements to the river water quality forecasting, but more interpretable, scalable, and data-efficient models are still required. The gaps will have to be addressed so as to facilitate future timely, and reliable management of water quality.

In the future, an apparent avenue for developing river water quality forecasting is by improving existing machine learning techniques and streamlining the data gathering process. This might involve the use of remote sensing technologies to make the process of data collection efficient, as well as the incorporation of advanced weather prediction models that would enhance the quality of meteorological inputs. Besides technical improvements, it can be recommended to increase the range of water quality indicators that are analyzed and the geographical and environmental range of applications in the future. It is important to note that the forecasting methods can be modified to be applied in tidal rivers and estuarine systems, which are dynamic and hence offer distinct challenges. Covering both methodological and more general implementation aspects, this review will help to design more robust and adaptive forecasting systems that could be run under increasing environmental and anthropogenic pressures. The knowledge contained in this paper helps not only to advance scholarly knowledge but also the basis on which intelligent, real-time water quality monitoring systems can be deployed around the world.

References

1. Li, X., Zhang, Y., & Liu, Y. (2020). *Remote sensing and machine learning for water quality monitoring in rivers: A review.* Water, 12(2), 350.
2. Chawla, R., & Mehta, S. (2021). Remote sensing-based water quality monitoring and forecasting. Journal of Hydrology, 596, 126098.
3. Kumar, P., Singh, J., & Kaur, H. (2020). ML algorithms in predicting river water quality. Water Resources Management, 34(11), 3671–3685.
4. Chen, L., Yang, S., & Liu, H. (2019). Prediction of river water quality using SVM and Landsat imagery. Science of the Total Environment, 688, 1366–1375.
5. Nguyen, H., Bui, D., & Pham, H. (2021). Deep learning for water quality prediction using remote sensing data. Computers & Geosciences, 150, 104735.
6. Sharma, A., & Goyal, R. (2021). Monitoring of the Ganga River using remote sensing and deep learning. Remote Sensing Applications: Society and Environment, 22, 100502.
7. Zhang, Q., Liu, Z., & Wang, X. (2023). Cloud-based AI system for real-time water quality assessment. Journal of Environmental Informatics, 41(1), 66–77.
8. Singh, A., & Patel, D. (2020). Satellite-based AI for river water monitoring. Environmental Monitoring and Assessment, 192(7), 431.
9. Hu, M., Zhao, J., & Li, F. (2022). Water quality mapping using UAVs and CNNs. Remote Sensing of Environment, 276, 113076.
10. Niu, Y., Wang, Z., & Han, J. (2021). Hyperspectral UAV and AI classification of river pollutants. Sensors, 21(5), 1658.
11. Das, P., & Ramesh, M. (2022). AI-based assessment of eutrophication using remote sensing. Environmental Modelling & Software, 148, 105244.
12. Fang, H., Wei, J., & Guo, Y. (2020). NDWI and random forest in river nutrient prediction. Ecological Indicators, 110, 105903.
13. Prasad, A., Mishra, D., & Ray, R. (2020). A hybrid AI model for river classification. Environmental Research, 184, 109351.
14. Wu, C., Zhang, Y., & Li, J. (2022). Genetic Algorithm-optimized ANN for water quality forecasting. Environmental Technology & Innovation, 27, 102393.
15. Halder, S., & Saha, P. (2019). WQI prediction using ensemble learning. Environmental Monitoring and Assessment, 191(8), 503.
16. Liu, R., Wang, Y., & Xu, H. (2021). CNN-LSTM deep learning for WQI prediction. Remote Sensing, 13(10), 1902.
17. Amini, A., Mohammadi, A., & Ghasemi, S. (2020). Challenges in remote sensing for water quality. Environmental Earth Sciences, 79(5), 173.
18. Zhang, F., & Zhang, D. (2021). Generalizability of ML models in hydrology. Journal of Hydrology, 596, 126048.
19. Ma, J., Xie, Z., & Liu, F. (2023). Data fusion for river water forecasting. Journal of Environmental Management, 315, 115163.
20. Rahman, S., Chowdhury, S., & Jahan, M. (2022). Explainable AI in environmental modeling. Environmental Modelling & Software, 149, 105284.