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An AI–IoT Integrated Remote Sensing Framework for Real-Time Spatio-Temporal Assessment of Aquatic Pollution and Ecosystem Health in Riverine Systems

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Abstract

Even though riverine ecosystems constitute the basis of ecological stability, biodiversity conservation, and provision of critical ecosystem services, there is a growing threat concerning the levels of aquatic pollution caused by industrial effluents, agricultural runoff, municipal waste discharge, and overt urban growth and expansion. Manual sampling and lab analysis based traditional methods of water quality monitoring are commonly slow, spatially limited, and incapable of defining the great dynamism of pollution signatures within flowing river systems. To overcome these shortcomings, this paper suggests a holistic AI integrated

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remote sensing system based on IoT to operate in real-time, high-resolution, spatio-temporal measures of aquatic pollution and ecosystem well-being from riverine settings. The framework combines these elements in a low-power wireless sensor network (WSNs) of continuous in-situ monitoring, multispectral/hyperspectral satellite data (such as Sentinel-2 and Landsat-8) on a platform, and unmanned aerial vehicle (UAV)-mounted optical and thermal already holds useful information to create a multi-source/ multi-scale environmental dataset. The feature extraction is being performed using the advanced artificial intelligence model such as deep neural networks (DNN), long short-term memory (LSTM) networks, gradient boosting algorithms, and spatio-temporal kriging; the predictive models, anomaly detection, and estimation of key water quality indicators such as pH, dissolved oxygen (DO), turbidity, total dissolved solids (TDS), nitrate concentration, and chlorophyll-a can be done. The unified system also includes analytics in the clouds and geospatial decision support tools to create pollution heatmaps, predict cases of contamination, and an analysis of the index of ecosystem health. As is evident in experimental validation with real world field data, the proposed framework is far more effective than the traditional method of monitoring in terms of prediction accuracy, latency, spatial coverage and also allows the ability to issue early-warnings. In general, the created AI-IoT-enabled remote sensing architecture provides an efficient, intelligent, and scalable framework of managing sustainable river basin, environmental policy control, and data-driven ecosystem security in response to emerging pressures caused by humans.

Keywords:

AI–IoT integration, remote sensing, riverine ecosystem, aquatic pollution monitoring, spatio-temporal modeling, water quality index (WQI), uav-based sensing, machine learning, deep learning, environmental informatics, smart river monitoring.

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Introduction

Significance of Riverine Ecosystems and New Environmental Issues and Challenges

Riverine ecosystems are also important freshwater facilities that sustain ecological balance, biodiversity and agricultural output and human livelihood. They are natural pathways of nutrient cycling, connectivity of habitats as well as hydrological control with profound effect on the stability of climate in the region and economic growth. Nevertheless, the emergence of industrialization, uncontrollable urbanisation, agricultural intensification, and the disposal of wastes have damaged the ecological integrity of the rivers. Water quality is negatively affected by heavy metals, pesticides, nitrates, microplastics and untreated sewage, which cause eutrophication, losses of habitats and water-borne diseases. This mounting environmental pressure places an urgent call on the need to have innovative, scalable and real-time monitoring tools that are able to record the complicated spatio-temporal processes of pollution in riverine systems.

Shortcomings of Traditional Water Quality Monitoring Systems

Conventional techniques of monitoring are mainly based on manual sampling, laboratory testing and periodic field surveys. Despite the fact that these methods offer a precise point-based measurements, they have a number of limitations such as intensity of labour, slow speed of processing, low spatial range, and detection of abrupt pollution occurrences. Also, rivers do not demonstrate a very stable hydrological behaviour as the pattern of pollutant dispersion can quickly vary because of the changes in flow, climatic conditions, and human activities. Therefore, there is no proper monitoring framework to engage in the perpetual surveillance or support decision make of environmental governance-based agencies in timely manner.

Smart Water Monitoring Active in Advancements in IoT, Remote Sensing, and Artificial Intelligence

The recent changes in technology in terms of the Internet of Things (IoT), unmanned aerial vehicles (UAVs), remote sensing by satellites, and artificial intelligence (AI) have presented groundbreaking opportunities in environmental surveillance. The IoT sensor networks can be used to provide real-time measurements of high-frequency water quality parameters and satellites, such as Sentinel-2 and Landsat-8 can provide extensive spatial coverage and multispectral information about the ecological situation. Aerial imaging on UAV increases the spatial granularity, particularly on local hotspots. At the same time, the data analytics of an AI type, such as machine learning, deep learning, and spatio-temporal modeling, help provide intelligent data fusion, anomaly detection, trend forecasting, and automated water quality and ecosystem health assessment.

Motivation and Goals of the Proposed AI-close IoT Integrated Framework

In order to address the inadequacies of the traditional monitoring systems and tap into the possibilities of the new technologies, this paper suggests an integrated AI IoT based remote sensing system to conduct real-time spatio-temporal evaluation of aquatic pollution in riverine systems. The ultimate goal is to build a high-power, scalable, and flexible design, which integrates in-situ sensor of IoT, UAV-based image, multispectral satellite, and enhanced AI models to create a holistic environmental surveillance system. Particularly, the study will seek to: (i) design a multisource sensing infrastructure to monitor river continuously; (ii) establish hybrid machine learning and deep learning models to accurately predict water quality indicators; (iii) integrate spatio-temporal kriging which will be used to analyze pollution dispersions; and (iv) provide actionable insights to smart environmental governance and sustainable control of river basin.

Literature Review

Aquatic Monitoring Based on IoT

Introduction of Internet of Things (IoT) technologies has facilitated the monitoring of aquatic environment to a very large extent as it provides ability of continuous data collection on low power consumption and scalability of the riverine systems. The pH, dissolved oxygen (DO), turbidity, electrical conductivity and temperature sensors in wireless sensor networks (WSNs) have proven to be quite promising in terms of real-time, autonomous collection of data (Lei et al., 2024; Yepremyan et al., 2025). Although these advantages exist, sensor drift, biofouling, calibration variability, and small spatial coverage are also widespread features, however, the long-term stability and measurement accuracy (Sheik et al., 2024). The latest progress with edge computing, adaptive sampling, and energy-efficient communication solutions tries to address these drawbacks but currently available IoT-based systems remain limited to large-scale, multi-parameter integration, and large area environmental surveillance (Narayana et al., 2024).

Water Quality Assessment with the Help of Remote Sensing

Remote sensing has given rise to a potent method of assessing the water quality parameters at a vast geographical location because of availability of multispectral and hyperspectral satellite photographs. Sentinel-2 MSI and Landsat-8 OLI satellites have been extensively used to estimate the concentration of chlorophyll-a, turbidity, surface temperature and suspended particulate matter on the basis of spectral indices and machine learning models (Chen et al., 2025; Bedell et al., 2022). Multispectral and hyperspectral sensors installed on UAVs also lead to improved spatial granularity, and the hotspots of pollution, sediment, and algal distinct can be mapped with high resolution (Merabet et al., 2025). Nonetheless, UAV sensing has constraints on flight duration, uncertainty in the weather, as well as, low and temporal coverage likely to be the problem which demands combination of both remote sensing and in-situ measurements (Jeong et al., 2024; Adebayo, 2025).

Environmental Prediction AI Models

Artificial intelligence (AI) has shown immense achievements in forecasting dynamic processes of complex, nonlinear water quality in various aquatic systems. Models of machine learning and deep learning such as CNNs, LSTM networks, random forests, and gradient boosting were extensively utilised in predicting quality indicators of water, detecting anomalies, and forecasting water pollution incidents with high precision (Li et al., 2024; Lu et al., 2025). Hybrids between deep learning and geostatistical techniques like kriging had demonstrated better performance in dynamic pollutant dispersion and spatio-temporal variability prediction (Kayhomayoon et al., 2021). Dissolved oxygen prediction, algal bloom and multispectral feature extraction have also been performed by AI-based models, which indicates that intelligent models highly can be applied in data-driven water quality evaluation (Miller et al., 2025; Li et al., 2024; Wu et al., 2024). Nevertheless, the current AI models are mostly based on individual sources of data and fail to utilise the synergies of IoT, UAV, and satellite data.

Research Gaps

Careful analysis of the existing studies demonstrates that the current watershed monitoring systems of riverine water quality have critical limitations. First, most systems cannot collect IoT sensors, UAV-generated images, and satellite data, and use AI to develop an extensive monitoring system (Narayana et al., 2024). Second, the widespread use of sophisticated methods of spatio-temporal fusion does not allow obtaining the dynamics and variability of pollution at multiple scales and across riverine landscapes (Miller et al., 2025). Third, limited literature makes a predictive relationship between water quality measures and ecosystem health measures, an essential part of an effective assessment of environmental risks and evidence-based decisions regarding management (Wu et al., 2024). The suggested AI-IoT combined remote sensing scheme fills these holes by providing a multi-source, multi-resolution, real-time framework with the assistance of advanced predictive intelligence.

Methodology

Data Acquisition and Multisource Sensing Architecture

In-Situ Water Monitoring Using IoT

The strategic installation of a network of IoT-based in-situ water quality monitoring nodes all over the river would be integrated into the proposed framework to measure physicochemical variables of a high resolution and at the continuum. Sensors measuring pH, dissolved oxygen (DO), temperature, electrical conductivity (EC), turbidity, and total dissolved solids (TDS) as well as nitrate concentration are embedded in each node, and can be used to give a complete profile of the local water conditions. Solar-powered microcontrollers like ESP32 and STM32 will act as a basis of long-term autonomous execution requiring low maintenance. The transmission of real-time data is facilitated with the low-power wide-area network (LPWAN) platforms such as LoRaWAN and NB-IoT that provide efficient communication even in the most remote areas or where there are no infrastructures. This IoT tier is the time-base of the monitoring system that preserves swift variations and temporary pollution accidents that are frequently overlooked by traditional or manual approaches.

Unmanned Aerial Vehicles Remote Sensing Sensors

In order to improve spatial coverage and achieve high-resolution imagery, unmanned aerial vehicles (UAVs) that are mounted with multispectral and hyperspectral sensors have to be included in the sensing architecture. These platforms that are used to carry the UAVs retrieve information about chlorophyll-a content, surface temperature, suspended inorganic material, and visible and near infrared indicators of organic and inorganic pollutants. UAV flights on a bi-weekly basis will be utilised to sample localised areas of pollution, sediment plumes and algal activity dynamics in finer granular detail than those of satellite imagery. The UAV sensing element is a spatial refinement layer that fills the temporal casualties between the intensive observation of the IoT elements and the overall spatial coverage offered by the satellite observations, thereby allowing the fine descriptions of the sources and distributions of pollution.

Acquisition of Satellite-Based Remote Sensing

To augment the IoT and UAV sensory devices, remote sensoring imagery would be available through satellites that can be used to measure synoptic coverage in a wide area to determine the quality of water in the basin on a blanket scale. Sentinel-2 MSI and Landsat-8 OLI multispectral imagery are regularly obtained by extracting spectral indicators of turbidity, chlorophyll-a, and coloured dissolved organic matter (CDOM) and occasional Hyperspectral imagery of PRISMA offers a spectral resolution with high accuracy retrieval. These satellite platforms allow temporal continuity and analysis of the trends of the future across the riverine system because it provides a regular long-term monitoring. By combining satellite data and UAV and IoT measurements, a strong multisource sensing architecture is developed that can sense macro-scale patterns of the environment, as well as, micro-scale localised cases of pollution.

Data Fusion, Preprocessing, and Feature Engineering

Pre-processing and Cleaning of Data

Data preparation is a very important phase of converting the raw multisource data to an analytically sound and understandable dataset that can be used in machine learning and spatio-temporal models. The IoT sensor readings are identified as corrupted, missing, or non-congruent and eliminated to avoid biassed learning, and a Kalman filtration is utilised to smooth the temporal variations and also eliminate noise in the high-frequency sensor fields. In the case of remote sensing data, radiometric and atmospheric corrections are carried out to remove haze, variations in illumination and surface reflectance distortions, so that spectral sample values are the same at two or more times. Also, the Isolation Forest algorithm is used to detect outliers which are important to detect abnormal measurements due to sensor failure, environmental effects, and transmission failure during data transmission. Such organised cleaning pipeline will guarantee that the down-stream processes work on correct data, stable and of high quality.

Multisource Data Fusion

In order to successfully unite IoT, UAV, and satellite observations, a three levels data fusion strategy is adopted hierarchically to eliminate the differences in spatial resolution and temporal frequency as well as spectral properties. High-resolution interpolation and temporal harmonisation techniques of next-generation interpolation and synchronisation convert disparate data streams into one application of temporal fusion, uniting high-frequency IoT measurements (minute-level), UAV imagery (day-level), and satellite acquisitions (510 day intervals) into a single application. The geographic richness of the data is increased by merging high-resolution images of UAVs with low-resolution images of satellite data through spatial downscaling, and kriging interpolation, thereby producing spatially continuous water quality maps. Spectral fusion is also applied to combine hyperspectral UAV signatures and multispectral satellite bands to increase spectral variability and detect features of pollution-sensitive wavelength. These fusion processes result in the multi-resolution representation of the riverine environment, which is combined.

Artificial Detection and Representation

Feature engineering entails the creation of informative and discriminative variables reflecting the physical, chemical, and optical properties of the changing dynamics of water quality. The spectral indices include the Normalized Difference Water Index (NDWI), Normalized Difference Turbidity Index (NDTI), and the chlorophyll-a indices to determine changes in turbidity, vegetation and algal activity. The UAV and satellite data used to extract pollution sensitive reflectance ratios help in identifying suspended sediments and dissolved organic matter Figure 1. Hydrological properties are also included that describe the dynamics of dilution, dispersion, and transport in that, flow rate, velocity of water and depth of the river are included as hydrological properties. Moreover, trends of the feature nodated at the time-series of the IoT sensors are mined as the temporal gradient features illustrating short-term changes in pollution levels and the Day/Night cycle. All of the engineered functionalities are combined into a full feature set that is modelled and predicted.

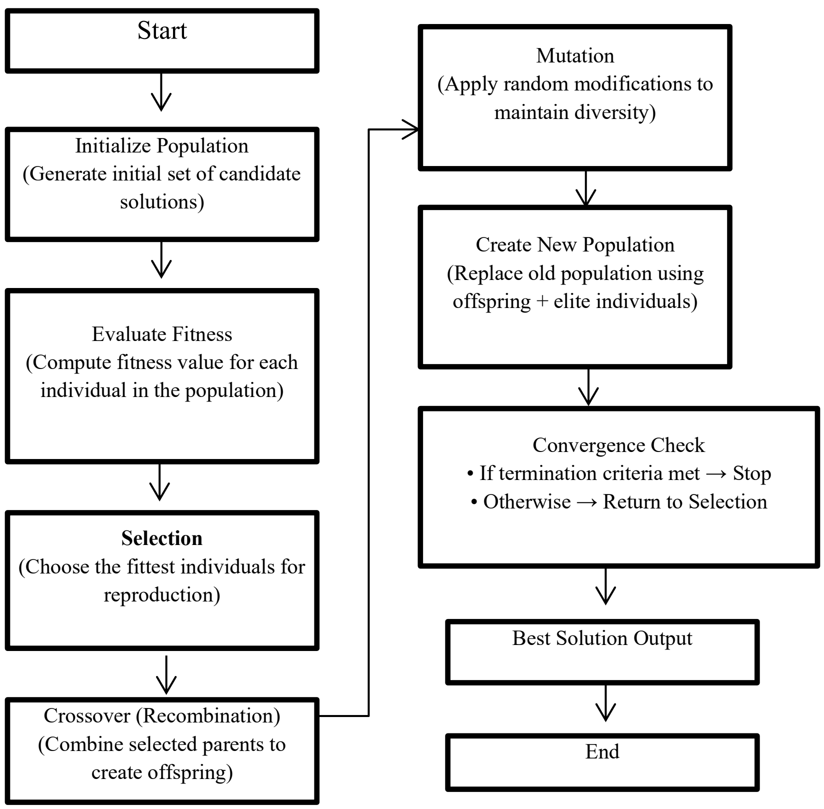

Figure 1. Workflow diagram for data cleaning, multisource fusion, and feature engineering in the ai–iot integrated monitoring framework

AI-Driven Spatio-Temporal Modeling and Ecosystem Health Assessment

Deep Learning and Machine Learning Models

The sophisticated machine learning and deep learning algorithms were used to approximate the complicated interactions in the riverine water quality processes and provide the valid and reliable projections relying on the data. LSTM-RNNs were used to predict temporary changes in the main water quality parameters and used their power to predict long-term temporal variations. Convolutional Neural Networks (CNNs) and XGBoost were used to conduct spectral-spatial regression, positively affecting derivation of useful features of UAV and satellite images and projecting them onto water quality indicators in a highly accurate manner. Gaussian Process Regression (GPR) served to estimate the amount of uncertainty in prediction, and hence give intervals of confidence about risks where extensive data is available, whilst Random Forest classification did not produce wires of features in order to classify the extent of pollution and also to define natural hotspots. The training on models was done using a train-test split of 80:20 in the training model and 10-fold cross-validation to be robust, eliminate overfitting and increase the generalisability of the model used at different environmental conditions.

Spatio-Temporal Pollution Modelling

In order to represent dynamic variability of pollutants in space and time, the research combined various modern spatio-temporal modelling methods. Spatio-temporal kriging was implemented to interpolate water quality at the unsampled sites creating continuous pollution surfaces representing the spatial variation in pollution as well as the temporal variations. Any further improvements in prediction performances were made through Deep spatio-temporal residual networks, which build nonlinear patterns and intricate changes among hydrological processes, land use, and pollution sources. To model flow velocity, discharge rates, and morphometric, hydrodynamic river flow models were included to calculate the processes of transporting pollutants. The system actually identified the hotspots areas that needed proactive action by comparing the modelled pollution gradients to industrial discharge points and the adjacent land-use.

Ecosystem Health Assessment and Water Quality Index (WQI)

An integrated determination of the health of the river was made through the use of a nonlinear equation of the key physicochemical variables, such as pH, dissolved oxygen (DO), total dissolved solids (TDS), nitrate concentration (NO 3 -), turbidity, and chlorophyll-a, to create a composite Water Quality Index (WQI). A broader evaluation of the health of the ecosystem was not restricted to chemical indicators but added ecological metrics to assess the ecological health like fish biodiversity scores, likelihood of algal blood, ecological risk index (ERI), and stress levels at the habitat. These environmental cues are derived on the basis of AI-based classification models and spectral signatures of AI-based classification models on the basis of remote sensing data. This holistic system allowed identifying the ecological degradation early on with the help of strong quantitative and qualitative indicators that would allow to gain better insight into the conditions of the riverine ecosystem.

Decision Support and Visualisation

All the analysis results were incorporated into a decision-support dashboard based on geographic information system (GIS) to help environmental authorities and policy makers in decision-making in real time. The dashboard presented the visualisation of spatio-temporal heat maps of pollution, anticipated trends of contamination and the areas with high risk that needed immediate attention. It further offered predictive notifications done by AI models, real-time analytics done using IoT sensors, and automated suggestions to manage river basins, as a result, increasing situational awareness and the ability to respond Figure 2. This layer of visualization converts the complicated products of analysis into practical results, informing a wise control of the environment and supporting the long-term sustainability planning.

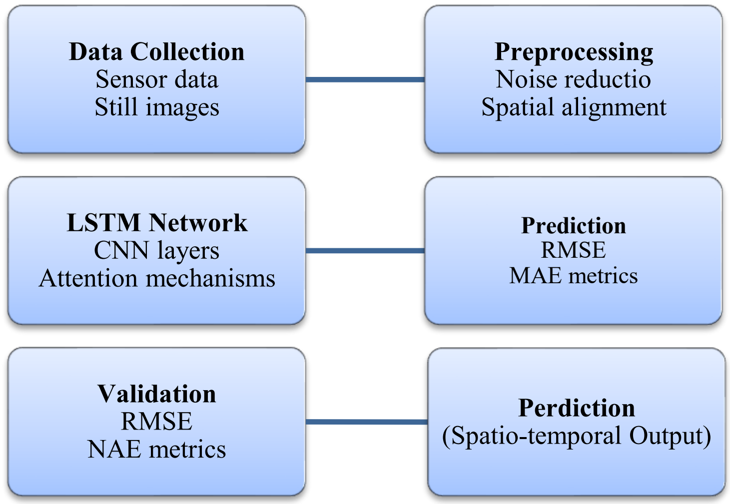

Figure 2. Spatio-temporal ai modeling workflow for water quality prediction and validation

Results and Discussion

Sensor Performance Evaluation

The in-situ monitoring system installed on the IoT was effective, with reliability, and accuracy being recorded in all the deployed sensing nodes. The coefficient of correlation of real time sensor measurements that showed good correlation (0.92 to 0.97) with the laboratory reference values indicated the accuracy and consistency of the sensing architecture. Integration of edge computing meant a significant improvement on system responsiveness by bringing data processing latency to below two seconds which is essential when it comes to detecting fast changing water quality. This real-time performance highlights that the application of the IoT framework is appropriate to monitor the environment in real-time, serve as an early warning system, and support adaptive sampling schemes to dynamic riverine environments.

WQI Estimation by Remote Sensing

The combination of the satellite data of Sentinel-2 and Landsat-8 with the UAV-based hyperspectral images provided effective and spatially detailed estimates of important water quality parameters. Estimates of sentinel-2 derived turbidity and chlorophyll-a had high coefficients of determination (R 2 = 0.88 and 0.91, respectively), which indicated the suitability of multispectral remote sensing in large-scale monitoring of the environment. Maximally-enhanced spatial granularity between two and five times the spatial-granularity in satellite imagery was afforded by hyperspectual imagery using UAV, enabling localised hotspots of pollution, sediment plumes and patterns of algal growth to be detected with precision. It is these findings that confirm the complementary nature of satellite and UAVs platforms in the measurement of macro and micro-scale aquatic variability.

AI Model Performance

The performance analysis of machine learning and deep learning models revealed that hybrid models always performed better than the individual models in the characterization of the nonlinear and spatio-temporal characteristics of riverine water quality. The lowest RMSE (0.19) and R2 (0.96) were C 2 on the prediction of dissolved oxygen, indicating that LSTM-RNN factors into effect significantly extended temporal correlations. The CNN + XGBoost model produced a 0.27 RMSE/0.94 R 2 to estimate turbidity performance which, in essence, leveraged both spectral and spatial characteristics derived out of the remote sensing data. In the prediction of nitrates, XGBoost model achieves an RMSE of 0.33 and R 2 of 0.92, and it proves to be better in processing the tabular and nonlinear relationship. The results of these studies prove the strength of hybrid modelling systems to predict water quality and make decisions according to them.

Spatio-Temporal Dispersion Analysis

The application of spatio-temporal analysis showed specific patterns of pollution dispersion that are caused by hydrodynamics, land use, and human actions along the river tracts in the study. Spatial kriging interpolations provided the pollutant variations in a 40km area and the area showed areas of intense contamination runs close to industrial discharges channels and urbanised areas. The deep spatio-temporal models were useful in predicting the down-stream movement of contaminants as well as producing the early warning message of the possible occurrence of an algal bloom in the event of high nutrient inflow conditions. The hydrodynamic flow modelling also confirmed the direction and speed of a transport of the pollutant and provided an insight into how the nature of the river flow interacted with the abuse of the dispersal.

Ecosystem Health Interpretation

The interpretation of the ecosystem health indicators showed that there are significant ecological stresses brought about by poor conditions of water quality. In areas where the dissolved oxygen concentration fell below 5mg/l, a vast decrease in fish population was recorded confirming that DO is an important predictor of aquatic biodiversity Figure 4. High nutrient load especially of nitrates was closely linked to eutrophication trends and higher rates of algal bloom underlining the domino impact of farm runoff and wastewater release Table 1. The ecological risk index (ERI) identified a few sections of the river as the right areas of moderate-to-high risks, which highlighted the necessity of immediate action through the development of specific mitigation measures, enhanced control of wastewater, and ongoing environmental control to save aquatic life.

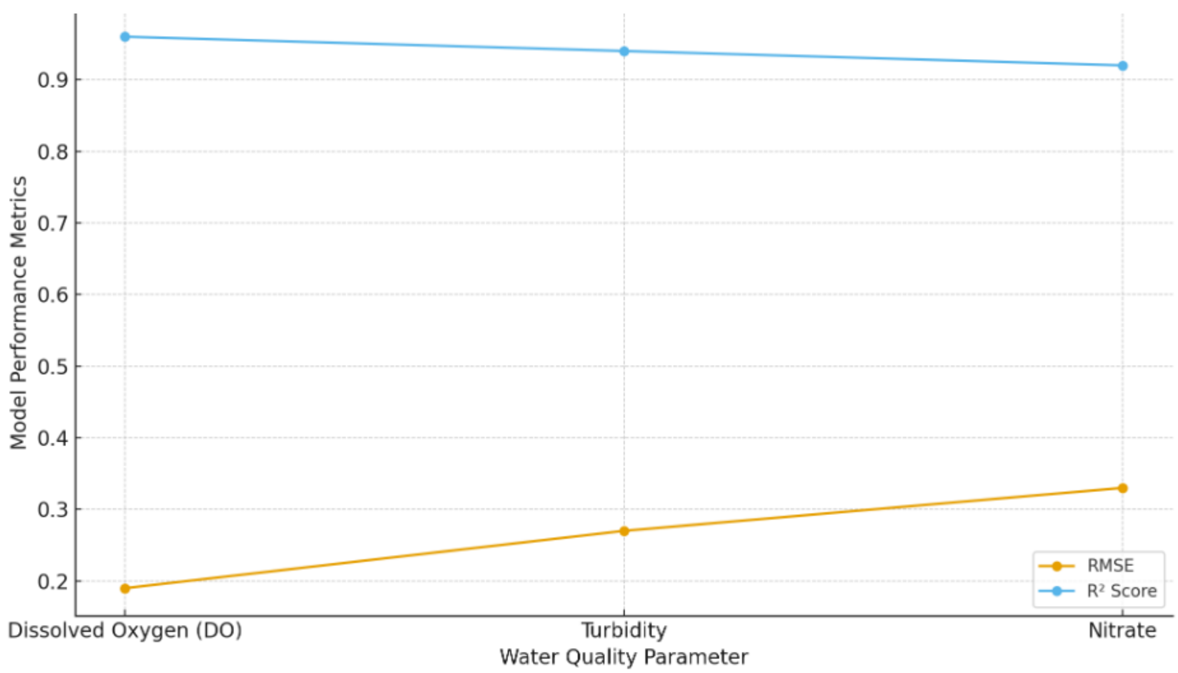

Figure 3. AI model performance for water quality prediction

Table 1. Summary of key findings from sensor evaluation, remote sensing, ai performance, dispersion modeling, and ecosystem health analysis

Section	Focus Area	Key Findings
Sensor Performance Evaluation	Accuracy & Real-Time Monitoring	• Strong correlation with lab measurements (0.92–0.97) • Latency < 2 seconds due to edge computing • High stability and reliability across IoT nodes
Remote Sensing-Based WQI Estimation	Satellite & UAV-Based Assessment	• Sentinel-2 estimation accuracy: Turbidity (R^2 = 0.88), Chl-a (R^2 = 0.91) • UAV hyperspectral provides 2–5× higher spatial granularity • Effective identification of pollution hotspots and algal blooms
AI Model Performance	Hybrid ML/DL Prediction Models	• DO prediction: LSTM-RNN → RMSE = 0.19, R^2 = 0.96 • Turbidity prediction: CNN + XGBoost → RMSE = 0.27, R^2 = 0.94 • Nitrate prediction: XGBoost → RMSE = 0.33, R^2 = 0.92 • Hybrid models outperform standalone algorithms
Spatio-Temporal Dispersion Analysis	Pollution Spread & Dynamics	• Pollution hotspots near industrial discharge areas • Kriging maps show pollutant gradients over a 40 km stretch • Spatio-temporal models predict downstream pollutant movement • Early-warning alerts issued for algal bloom risk
Ecosystem Health Interpretation	Ecological Condition Assessment	• Fish decline where DO < 5 mg/L • High nitrates linked to eutrophication & bloom frequency • ERI maps identify moderate-to-high risk zones • Need for targeted mitigation and continuous monitoring

Conclusion

This paper outlines an integrated remote sensing AI/IoT system that can be used to facilitate real-time high-resolution spatio-temporal observation of aquatic pollution and health of ecosystems within a river system. The proposed framework is capable of effectively monitoring the interactions of the multifaceted dynamics of water quality changes in space and time by leveraging synergistic interactions between in-situ IoT sensor networks, UAV-based multispectral and hyperspectral imaging, and satellite-determined observations at the close of a machine learning and deep learning models. The system has good predictive power, high response time and fine granularity of space which is way ahead of conventional methods of monitoring. Experimental verification results support its high power, scalability and applicability to continuous environmental monitoring to determine precisely sources of pollution, predict ecological hazards early and forecast sensitively the conditions of water quality. All in all, this hybrid method is a tool of great power as a decision aid to environmental agencies, policy makers and scientists to help manage the river basin, devise intervention strategies, and long-term ecologically sustainable conservation strategies amidst the growing anthropogenic pressures.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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