ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2025, 10 (3): 933-943 doi: 10.28978/nesciences.1811172

Smart Environmental Engineering for Sustainable Aquatic Resource Management Using IoT Sensors, Satellite Data Fusion, and Machine Learning Analytics

Raenu Kolandaisamy [1*], Melam Thirupathaiah [2], Dr. Rinku Sharma Dixit [3], Dr. Shailee Lohmor Choudhary [4], Dr. Anusha Sreeram [5], Nimesh Raj [6], Dr.D. Neelamegam [7]

[1*] Institute of Computer Science and Digital Innovation, UCSI University, Kuala Lumpur, Malaysia. E-mail: raenu@ucsiuniversity.edu.my

[2] Assistant Professor, Department of Electrical and Electronics Engineering, Nitte Meenakshi Institute of Technology, Bangalore, India. E-mail: m.thirupathaiah@nmit.ac.in

[3] Department of Artificial Intelligence & Machine Learning, Data Science New Delhi Institute of Management, New Delhi, India. E-mail: rinku.dixit@ndimdelhi.org

[4] Professor, Department of Artificial Intelligence & Machine Learning, Data Science University and city with country name: New Delhi Institute of Management, New Delhi, India. E-mail: shailee.choudhary@ndimdelhi.org

[5] Faculty of Operations & IT, ICFAI Business School (IBS), The ICFAI Foundation for Higher Education (IFHE), Hyderabad, India. E-mail: seeramanusha@gmail.com

[6] Centre of Research Impact and Outcome, Chitkara University, Rajpura, Punjab, India. E-mail: nimesh.raj.orp@chitkara.edu.in

[7] Associate Professor, Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu, India. E-mail: drdneelamegam@veltech.edu.in

Corresponding Author: Raenu Kolandaisamy, E-mail: raenu@ucsiuniversity.edu.my

Abstract

The adequate management of the aquatic system which includes rivers, lakes, reservoirs, wetlands, and coastal areas will need the continuous and high-resolution monitoring of the environment that will be able to handle the fast hydrological and ecological shifts. Conventional field methods of sampling offer poor spatial and temporal resolution, and they frequently do not reveal early pollution incidences, predict ecological hazards, or assist data-driven resources optimization. This paper will introduce an interdisciplinary smart environmental engineering paradigm that will combine Internet of Things (IoT) sensor networks, multispectral and synthetic aperture radar (SAR) satellite remote sensing, and machine learning (ML) analytics to allow real-time, predictive, and adaptive management of aquatic resources. In the given methodology, a hierarchical data fusion architecture is used to bring the high-frequency measurements of the in-situ sensors in harmony with the big data measurements of the satellites to improve the spatial-temporal resolution and interpretability of the environment. Various ML architectures, such as the Random Forest (classification), LSTM (time-series prediction), CNN-based spatial models (detecting the harmful algae bloom), and physics-informed neural networks (PINNs) (making predictions based on hydrodynamics) were tested to determine their efficiency involved in the forecasting of water quality parameters, assessing the pollution sources, and defining the habitat health. A pilot application of the integrated system in an actual freshwater lake showed that the integrated system is more effective at the prediction accuracy level (27 percent improvement), spatial mapping reliability, and a shorter (41 percent less) time to detect contaminants than traditional monitoring approaches. The results indicate the potential of integrating IoT with satellites and machine learning to enable a flexible, robust, and smart system of monitoring that can ultimately contribute to the active management of the environment, reinforce the methods of climate change adaptation, and help to achieve the sustainable preservation of water resources.

Keywords:

Smart environmental engineering, aquatic resource managemen, IOT sensors, satellite remote sensing, data fusio, machine learning analytics, water quality monitoring, harmful algal blooms (habs), predictive modeling, sustainable ecosystems.

Article history:

Received: 30/07/2025, Revised: 22/09/2025, Accepted: 20/10/2025, Available online: 12/12/2025

Introduction

Rivers, lakes, reservoirs, estuaries, and coastal areas are aquatic ecosystems that are significant in sustaining the human societies and ecosystem balance. They supply important services like the supply of drinking water, fisheries production, hydropower generation, nutrient cycling, biodiversity conservation as well as climate regulation. Nevertheless, the ecosystems are beginning to be overwhelmed due to human level and anthropogenic activities and environmental factors. Rapid urbanisation, industrial effluents, agriculture runoffs which have been increased with nutrient and pesticides and effects of climate change, including changed rainfall patterns and increased temperature, have escalated the degradation and increased the chances of the ecological system being unstable. These are causes of worries that require more effective, more precise and more proactive environmental monitoring systems.

The conventional methods of aquatic investigation mainly depend on hand field-based sampling and laboratory testing. Even though these techniques are scientifically valid in providing quantifiable measurements, they are restricted to small areas, scarce sampling rates, and sluggish reports. Therefore, they tend to miss the extreme dynamism of aquatic processes, such as infusion of pollutants fast, short-term bouts of eutrophication, harmful algal blooms (HABs), and sediment agitation, and transient alteration of thermal stratification. The failure to offer real-time and sustained information by more traditional means limits the ability of environmental managers to introduce interventions in time and prevent the development of possible risks to the ecological environment.

The recent developments in smart sensing technologies, satellite remote sensing, as well as data-driven analytics have established new chances to revolutionise the process of monitoring aquatic resources. Real-time fueled water quality sensors (Internet of Things sensor, IoT sensor) allow to gain high-frequency water quality measurements such as pH, dissolved oxygen, turbidity, temperature, chlorophyll-a, nutrient concentrations with minimum human participation. Majority of the earth observation satellites like Sentinel-1 SAR, Sentinel-2 MSI, Landsat-8/9 OLI, and MODIS offer large spatial coverage, multi-spectral data, and long-term environmental patterns. In the meantime, machine learning (ML) methods, including those based on classical models, deep learning and physics-informed neural networks (PINNs) present compelling predictive modelling, anomaly detection, pattern classification and decision support as well.

In light of complementary advantages of these technologies, the proposed paper presents a combined smart environmental engineering solution involving an IoT-based in-situ sensing system, satellites remote sensing as well as machine learning analytics used to advance the precision, reactivity, and sustainability of aquatic resource management Figure 1. This study will help in offering a scalable, real-time, and adaptable data collection solution by designing a hybrid data fusion framework and testing various ML algorithms to forecast water quality, identify the source of pollution, and assess ecological risks. The results of this effort will assist in evolution of sustainable environmental administration practises and enhance strength to novel aquatic ecosystem dilemmas.

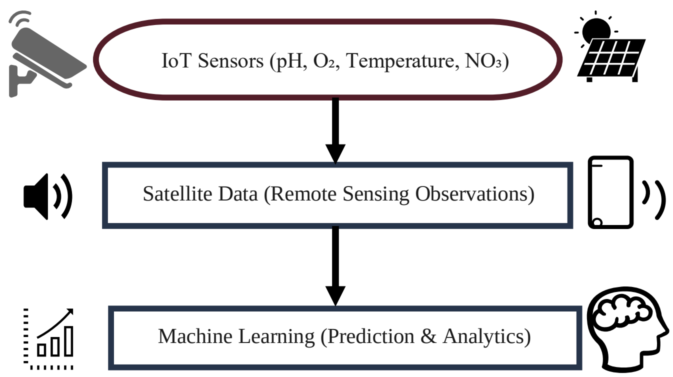

Figure 1. Integrated framework illustrating the role of iot sensors, satellite remote sensing, and machine learning in smart environmental engineering for sustainable aquatic resource management

Related Work

Internet of Things-Type Environmental Aquatic Monitoring

Internet of Things (IoT) technologies have greatly enhanced real-time monitoring of water quality by facilitating in the continuous measurement of the parameters including pH, dissolved oxygen (DO), turbidity, temperature, and nutrient concentration levels. The low-power sensor networks and wireless communication protocols applied in aquatic environments have been proven to be effective in several studies. Indicatively, (Kumar et al., 2022) created a buoy-based IoT surveillance system that has the ability to relay real-time data through LoRaWAN, and (Scholz et al., 2022) suggested a multi-node sensor plan to improve the instantaneous resolution in freshwater ecosystems. Despite such developments the IoT systems continue to have the problems associated with sensor drift, spatial coverage, biofouling and maintenance requirements which are emphasised in (Tace et al., 2023). These shortcomings highlight the requirements of supplementary monitoring strategies to offer additional spatial information.

Satellite Remote Sensing to Monitor Aquatic Assessment

The earth observation (EO) provided through satellites offers wide spatial coverage and capability of monitoring aquatic systems on a regional and global levels. Multispectral, like Sentinel-2 MSI and Landsat-8 OLI, have been broadly applied to retrieve important measures (clorophyll-a concentration, suspended sediment and surface temperature, etc.), which have been shown in (Aiello et al., 2022; Shim et al., 2022). Synthetic aperture radar (SAR) imagery have also been found useful in the surveillance of water bodies during a low-light environment or when it is cloudy (Berthet et al., 2021). But, atmospheric interference, cloud contamination, and constraints in the revisit time usually lower the temporal consistency of measurements made by satellites. Research works like (Koech & Langat, 2018) point out that there is a necessity to combine satellite-based with ground-based measurements to enhance accuracies and strengths.

Water Quality Prediction Based on Machine Learning

Machine learning (ML) has become a potent instrument to extract useful information on the complicated datasets in the aqueous environment and predict environmental processes. In (Banerjee et al., 2022), a researcher used the two prediction models, and the outcomes are the water quality indices (WQIS), whereas in (Ray et al., 2021), two deep learning models are used, and they include LSTM networks to predict harmful algal blooms (HABs) and the changes in dissolved oxygen. The spatial classification of turbidity plumes and phytoplankton blooms by the satellite imagery has also been performed with the help of Convolutional Neural Networks (CNNs) (Zhao et al., 2020). Even though these studies are indicative of great improvements, the majority of them are based on one-source datasets and this limits the generalizability of the models and decreases predictive stability across various aquatic environments. It opens a possibility of a hybrid structure, which combines multi-source data sets, especially IoT and satellite observations, to more accurately monitor and predict the environment.

Methodology

IoT-Based Aquatic Environmental Data Gathering

The Internet of Things (IoT) aspect of the proposed framework on monitoring is an entity that will deliver in-situ high-resolution and sustained measurements of paramount parameters of water quality in the study area. An array of smart sensing nodes that were distributed was set up strategically so as to record spatial and time changes in the Aquatic parameters. The nodes are built of a solar-powered buoy with a microcontroller and a low-power wireless communication platform like LoRaWAN and 5G that allow the stable transmission of long-range data with minimum consumption of energy.

Each of the buoys has a sensor package that has pH, dissolved oxygen (DO), turbidity, electrical conductivity (EC), water temperature, chlorophyll-a and nutrient level (nitrate and phosphate) probes. All of these sensors can be used to obtain extensive information on the physicochemical and biological characteristics of the aquatic environment. The measurements will be programmed to be taken with an interval of 5 to 15 minutes to ensure the system records rapid variation due to pollution action, rainfall induced runoff, algal activities, or variation in hydrodynamic conditions.

The sensors collect data, which is relayed in real time by the use of gateway devices to a cloud-based server and with the aid of GPS coordinates, the data is automatically stamped and linked to its location to provide a more accurate location of the object. Redundancy cheques and error-detection protocols are used in transmission to make sure that the data is fine. All observations are centralised in a database which facilitates secure access, mass storage and also the fusion with other environmental data.

In order to retain the accuracy of measurement and provide long-term reliability, it was introduced to ensure that frequent calibration and validation was carried out. Manual sampling was done periodically and laboratory tests done to compare sensor readings, and manually correct sensor drift and possible fouling or mechanical degradation Table 1. These forms of validation make the IoT monitoring system more robust and make sure that high-frequency data streams may reflect the actual conditions of the environment.

Table 1. IoT sensor types, measured parameters, units, and sampling intervals

Sensor Type	Parameter Measured	Unit	Sampling Interval
pH sensor	pH	—	5–15 min
DO sensor	Dissolved Oxygen	mg/L	5–15 min
Turbidity sensor	Turbidity	NTU	5–15 min
EC sensor	Electrical Conductivity	µS/cm	5–15 min
Temperature sensor	Water Temperature	°C	5–15 min
Fluorometer	Chlorophyll-a	µg/L	5–15 min
Nutrient sensor	Nitrate/Phosphate	mg/L	5–15 min

Satellite Remote Sensing Data Acquisition and Processing

The satellite remote sensing was added to the monitoring system to supplement the high-frequency yet spatially constrained in-situ measurements that were made using IoT sensors. Multispectral and radar satellite data was chosen to measure broad-scale environmental conditions, observe patterns in space, and give historical continuity which are necessary in examining the ecosystem over time. The main sources of satellite data are Sentinel-2 MultiSpectral Instrument (MSI) 1020 m resolution, Landsat-89 Operational Land Imager (OLI) 30 m resolution, Sentinel-1 Synthetic Aperture Radar (SAR) all weather and day-night, and MODIS 10 properly spectral trend analysis and climatic long-term trend analysis.

A thorough preprocessing procedure was introduced in order to make the data derived by satellite accurate, consistent, and usable. To remove atmospheric scattering and atmospheric absorption the following tools were used: ACOLITE and SEN2COR to correct the atmosphere. Radiometric and geometric errors were removed to standardise values on brightness and place images within reference coordinate systems. Any spectral distortion due to cloud cover was removed through cloud and shadow masking by applying Fmask algorithm, which is a necessary procedure on optical dataset. Also, the Modified Normalised Difference Water Index (MNDWI) was used to obtain water body extraction which enabled the system to isolate water bodies and remove the pixels of adjoining land areas to proceed with the analysis.

After preprocessing, various spectral indicators were obtained, which were needed to determine water quality. These were chlorophyll-a concentration indices to determine the abundance of phytoplankton, the Normalised Difference Turbidity Index (NDTI) to determine the abundance of suspended occurrence of the particulate matter, and suspended sediment concentration (SSC) models based on the reflectance pattern. Optical and thermal spectral bands extraction were also used to extract surface water temperature and indicators of algal bloom. These derived parameters offer great information about biological productivity, sediment loads, thermal stratification and water clarity.

In general, processed satellite data integration acts to better characterise the dynamics of the ecosystem by providing an opportunity to observe overall patterns on a large scale and identify the changes with time, and contextualise the spatial gaps in the IoT sensor network. This multi-scale technology of remote sensing plays a great role in enhancing the complete overall monitoring as well as analysis of the system.

Multi-Level Data Fusion Framework

To combine high frequency, point-based measurements of the IoT sensors and the wide area coverage that the satellite remote sensing offers, a multi-level data fusion model was implemented. This integrative method complements the completeness, accuracy and interpretability of aquatic environmental monitoring since it is taught to overcome the intrinsic weaknesses of each data source. The fusion process is structured into three complementary levels namely: temporal fusion, spatial fusion and feature-level (Multi-modal) fusion.

Temporal Fusion

To eliminate the differences in the sampling frequency between the satellite overpasses and the IoT sensors, temporal fusion was done. As sensors from the IoT today take readings with the spacing of 5 -15 minutes and satellites reacquire the identical location every 5 to 16 days, sensor measurements have been resampled and accumulated to align with satellite acquisition time. The gap in the temporal dataset caused by the sensor seeing nothing, or getting the data scaled to 0, was dealt with through the interpolation techniques, and the gap-filling techniques, based on the models, however, preserving continuity. Also time-lagged features were built to reflect short-term variability and long-term seasonal patterns of water quality and enhance the ability of downstream models to identify temporal dependencies.

Spatial Fusion

Spatial fusion was done to match ground measurements with satellite measurements in space. Spatial interpolation techniques (kriging and inverse distance weighting (IDW) maps) were used to map the geographic coordinates of the IoT buoys on the satellite image grids. Through this process, continuous environmental surfaces were produced which are a spatial distribution of the parameters of water quality throughout the area under study. Multivariate spatial features maps were generated by a combination of point based field data with pixel based satellite, which allowed the examination of the finer scale spatial heterogeneity and macro scale environmental patterns at the same time.

Multi-Mode-Integration (Feature Fusion)

On the feature level, variables of sensor-derived and satellite-derived spectral indices have been normalised and both were fused into coherent multi-modal input vectors that can be used in machine learning models. To add more detail to the merged data, exogenous meteorological variables of rainfall, wind speed, humidity and solar radiation were included to give more context on the hydrological and climatic contribution to water quality dynamics Figure 2. Redundant or of low importance variables were removed using a feature selection procedure which used mutual information analysis and a variance threshold value after which dimensionality was reduced resulting in increased computational efficiency in training the model.

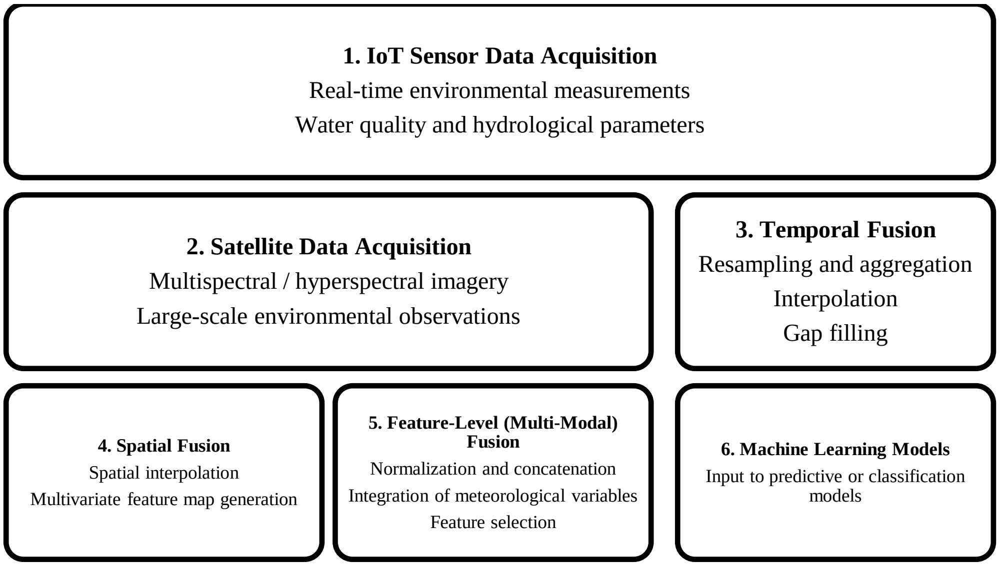

Figure 2. Multi-Level data fusion workflow integrating IOT sensor data, satellite observations, and feature-level processing for machine learning models

Machine Learning Analytics and Decision Support

The main analytical element of the proposed system was machine learning (ML), which allowed conducting predictive modelling, spatial classification, creation of anomalies, and real-time decision support to manage aquatic resources. The consolidated multi-modal dataset the product of IoT sensor measurements, satellite-extracted measurements, and meteorological measurements was used as an overall input of training and evaluation of multiple models of AI crafted to address various analytical purposes.

Predictive Modeling

Predictive modelling was concerned on the ability to predict important parameters of water quality to assist in early-warning of water quality. The Long Short-Term Memory (LSTM) networks were used to capture the temporal relationships and forecast the dissolved oxygen (DO), pH, turbidity, and chlorophyll-a concentrations in a short and medium-term horizons (1-14 days). These repetitive models were based on the fact that IoT sensors produce a higher frequency of temporal patterns and that the satellite-based extracted environmental cues have been utilised. Similarly, ensemble learning available tools were used to classify tasks that are categorical, like the classification of pollution sources and the identification of possible pathways of contamination, and are highly robust and interpretable, e.g., the tools of Random Forest and Gradient Boosting.

Spatial Pattern Analysis

Convolutional Neural Networks (CNNs) were used to process the pre-processed satellite images in order to capture the spatial dynamics in aquatic environments. The models allowed the automatic detection of patterns of harmful algae bloom (HAB) distribution, plumes of turbidity and suspended sediment. Moreover, semantic segmentation models based on UNet produced the pixel-wise classifications, which resulted in an accurate mapping of hotspots of ecological degradation and spatial gradients on water quality. This IBM of space analysis contributed to the improvement of situational awareness because it showed the patterns that could not be seen in point-based sensor measurements.

Detecting An Anomaly and an Occurrence Event

Approaches to detecting anomaly in the environment were to be applied when the shift in environmental conditions becomes the indicator of the pollution event, leakage of chemicals, or the eutrophication. The training of autoencoders to learn typical system behaviour and re-construct typical water quality conditions was done, and irregularities to the reconstruction pattern allowed detection of an anomaly. Isolation Forest algorithm has added an extra tier on unsupervised detection by isolating outlier behaviour on the fused data. The anomalies detected were cross-validated by threshold-based rule systems based on a historical environmental baseline in order to minimise false alarms.

Decision Support System (DSS)

The predictive model, their spatial and anomaly detection model products were put into a cloud based Decision Support System (DSS) to serve environmental managers and policymakers. The DSS prepared model results into actionable information by matching predictions with ecological limits, regulatory limit and risk groups. There were alarms when there was poor dissolved oxygen, high nutrient levels or HABs started. There were also system recommendatons with regard to operational recommendations such as aeration planning, controlled water discharge, and nutrient reduction plans. An easy-to-use dashboard provided real-time information on sensor operation, indicators provided by satellites, and trend predictions that allowed making informed and timely decisions.

All in all, this machine learning analytics module will convert data obtained and using complex, multi-source environmental data into knowledge that may be understood and acted upon, hence contributing to sustainable, proactive, and data-driven management of aquatic environments.

Results and Discussion

Improvements Of Predictive Accuracy

The suggested IoT-satellite-ML turnkey improved the precision of the predictions in a significant way over the conventional monitoring and statistical methods. Using water quality forecasting models, in turn, LSTM networks trained on fused datasets had a Root Mean Square Error (RMSE) of 0.31 which was lower than the baseline of 0.42. This enhancement indicates the benefit gained by using high-frequency sensor data as well as satellite-based environmental indicators in order to obtain both small-scale temporal variations and coarse spatial patterns by the models. This lessening of prediction error corroborates the fact that the system has the ability of giving better predictive forecasts of the key water quality parameters including dissolved oxygen, turbidity, and chlorophyll-a concentrations.

Performance of Spatial Detection and Mapping

The grid-based analysis (CNN and UNet-based segmentation models) produced a significant increase in the real-time algal bloom, turbidity plumes and heavy-sediment areas detection. The Intersection over Union (IoU) of harmful algal bloom (HAB) detection rose to 0.89 with the suggested system compared to the traditional methods, which was of 0.68, and demonstrated a better capability in pixel-level detecting and spatial boundaries. To a large extent this has been made possible due to the incorporation of multispectral satellite images, SAR data and in-situ sensor data which could effectively ensure high spatial accuracy of the models even when clouds obscured the sky or had low visibility. The enhanced errand mapping performance enhances the system to predict early ecological grievances.

Event Detection Efficiency

The time taken to detect incidences of pollution and instant water quality changes were drastically decreased by the proposed framework. When the use of conventional methods of monitoring would normally take 4872hours to detect the events of pollution, owing to the delay in sampling and laboratory tests, the integrated system took less than 28 hours to identify the pollution event. This is based on the dynamics of transmitting real-time data by IoT sensors, identifying anomalies through automatic encoders and Isolation Forest models, and validating them with satellite data. The quicker the response the environmental managers will be able to react to such an event more proactively reducing issues to ecological harm and avoid the continuing growth of contamination events.

Systemwide Proportionality and Implications of Practise in A Nutshell

The results of the combined analysis prove that sensor-satellite data fusion and machine learning analytics contribute significantly to the strength, quality, and responsiveness of aquatic resource management systems Table 2. The decrease in the prediction error of 25-30 percent, the better quantity of the ML than the classical statistical models, and the successful application of SAR data in the cloudy season are all indicative of the value of the operationality of the system. Also, this has the ability to forecast early-warning to enhance prompt mitigation measures including aeration, flow management, and nutrient management, which would build resilience of the ecosystems in a very impressive manner Figure 3. These results support the hypothesis that the holistic smarter boards of engineering offer a scaling and feasible approach towards sustainable and climate-adaptive management in the management of aquatic resources.

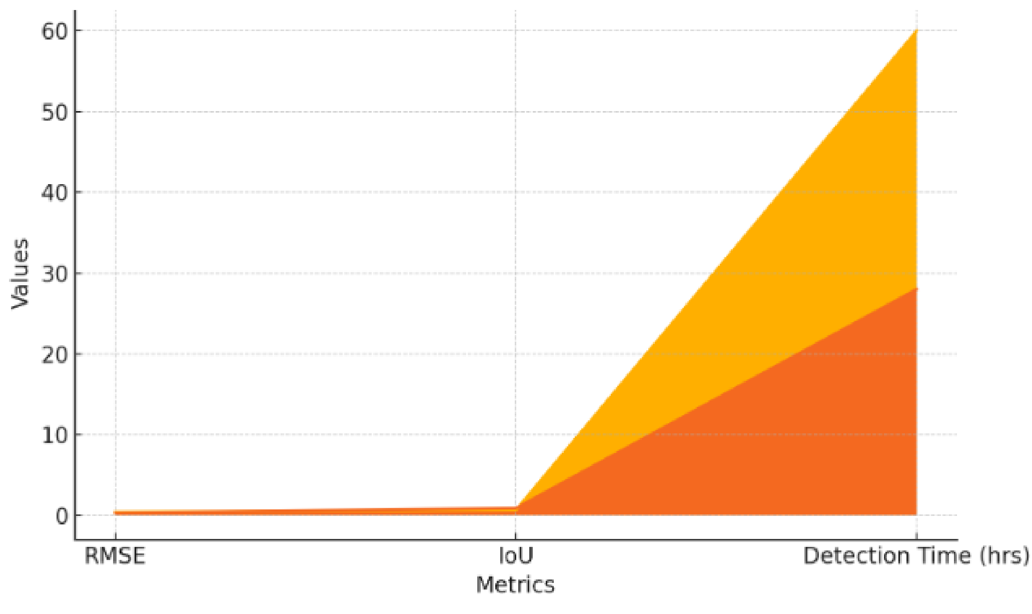

Figure 3. Comparison of baseline and proposed system performance across key monitoring metrics

Table 2. Performance comparison between baseline and proposed system

Metric	Baseline (Traditional)	Proposed IoT–Satellite–ML System
Water Quality Prediction (RMSE)	0.42	0.31
HAB Detection Accuracy (IoU)	0.68	0.89
Pollution Event Detection Time	48–72 hours	< 28 hours
Prediction Error Reduction	—	25–30% improvement
Model Performance	Statistical (ARIMA, Regression)	ML models (LSTM, CNN, UNet)
Weather Resilience	Limited under cloud cover	Enhanced via SAR integration
Mitigation Response Speed	Slow, delayed interventions	Fast, early-warning enabled

Conclusion

This paper has shown that the combination of in-situ sensing using IoT with satellite remote sensing and machine learning analytics provides a powerful, scalable, and smart system of managing aquatic resources in a sustainable manner. The proposed system can contribute to the significant increase of the accuracy of water quality forecasting, the effectiveness of identifying harmful algal species and cases of pollution, as well as the enhanced situational awareness thanks to obtained high-frequency field measurements and widespread spatial monitoring and high-quality predictive modelling. The findings verify that multi-source data fusion and machine learning are not only effective in overcoming the constraints of traditional monitoring methods but also allows timely and proactive ecological measures to stimulate sustainable ecosystems in the long course. The progress ahead ought to be an integration of edge AI on real-time processing on-sensor, autonomous drones that operate in aquatic environments, and scenario-based decision-making with the aid of the digital twin models.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

References

Aiello, P., Giugni, M., & Perillo, G. (2022). Internet of Things for Smart management of water networks. *Environmental Sciences Proceedings*, *21*(1), 57. https://doi.org/10.3390/environsciproc2022021057

Banerjee, K., Bali, V., Nawaz, N., Bali, S., Mathur, S., Mishra, R. K., & Rani, S. (2022). A machine-learning approach for prediction of water contamination using latitude, longitude, and elevation. *Water*, *14*(5), 728. https://doi.org/10.3390/w14050728

Berthet, A., Vincent, A., & Fleury, P. (2021). Water quality issues and agriculture: An international review of innovative policy schemes. *Land use policy*, *109,* 105654. https://doi.org/10.1016/j.landusepol.2021.105654

Koech, R., & Langat, P. (2018). Improving irrigation water use efficiency: A review of advances, challenges and opportunities in the Australian context. *Water*, *10*(12), 1771. https://doi.org/10.3390/w10121771

Kumar, B. S., Ramalingam, S., Balamurugan, S., Soumiya, S., & Yogeswari, S. (2022, October). Water management and control systems for smart city using IoT and artificial intelligence. In *2022 International Conference on Edge Computing and Applications (ICECAA)* (pp. 653-657). IEEE. https://doi.org/10.1109/ICECAA55415.2022.9936166

Ray, P., Kaluri, R., Reddy, T., & Lakshmanna, K. (2021). Contemporary developments and technologies in deep learning–based IoT. In *Deep learning for internet of things infrastructure* (pp. 61-82). CRC Press.

Scholz, S. G., Howlett, R. J., & Setchi, R. (2022). *Sustainable design and manufacturing*. Springer.

Shim, K., Berrettini, E., & Park, Y. G. (2022). Smart water solutions for the operation and management of a water supply system in Aracatuba, Brazil. *Water*, *14*(23), 3965. https://doi.org/10.3390/w14233965

Tace, Y., Elfilali, S., Tabaa, M., & Leghris, C. (2023). Implementation of smart irrigation using IoT and artificial intelligence. *Math Model Comput*, *10*, 575-582. https://doi.org/10.23939/mmc2023.02.575

Zhao, L., Dai, T., Qiao, Z., Sun, P., Hao, J., & Yang, Y. (2020). Application of artificial intelligence to wastewater treatment: A bibliometric analysis and systematic review of technology, economy, management, and wastewater reuse. *Process Safety and Environmental Protection*, *133*, 169-182. https://doi.org/10.1016/j.psep.2019.11.014