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Artificial Intelligence-Enabled Monitoring Framework for Aquatic Ecosystem Changes Prediction and Conservation Decision Support

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Abstract: Aquatic ecosystems face increasing levels of pollution, environmental variability, and ecological stress, making intelligent monitoring and future conservation planning necessary. ThisThis research seeksseeks to design an AI-based framework to predict changes in aquatic ecosystems, evaluate risks in these environments, and support conservation decisions. Our framework combines multi-source aquatic environmental observations together with data preprocessing, feature engineering, AI-based prediction, Ecosystem Risk Index (ERI) evaluation, and decision-making support for conservations. Random Forest, XGBoost, and Long Short-Term Memory (LSTM) models were compared with the proposed framework on Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The proposed framework outperforms the other methods in terms of MAE (0.184 vs. 0.286 in Random Forest; 0.231 in XGBoost; 0.247 in LSTM) and (R^2) (0.94 vs. 0.86 in Random Forest; 0.91 in XGBoost; 0.89 in LSTM). Environmental Risk Index (ERI) values ranged between 0.24 and 0.71, with the maximum value obtained for the period P8, showing relatively high environmental risk. The findings reveal the capability of incorporating an AI-based forecast with ecosystem risk assessment to detect changes in aquatic environment conditions and guide the process of monitoring efforts. Future research is needed to validate the concept via field observations, IoT technology, remote sensing, and other data sources.

Keywords: Artificial Intelligence; Aquatic Ecosystems; Environmental Monitoring; Ecosystem Risk Assessment; Predictive Modeling; Conservation Decision Support; Environmental Data Analytics.

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I. Introduction

Aquatic ecosystems are important for maintaining environmental diversity, ecological balance, and sustainability. These ecosystems are currently being threatened by pollution, climate change, eutrophication, habitat loss, and biodiversity loss. The conventional environmental monitoring systems, which rely on sample collection and manual observations, may be limited in their ability to monitor changing environments and complex ecosystem dynamics. This is due to the integration of artificial intelligence, Internet of Things, and remote sensing technologies, which can support continuous monitoring and assessment (Ananthi et al., 2026; Miller et al., 2025; Rella et al., 2026).

Recent studies using artificial intelligence show that the technology is useful in conducting autonomous underwater monitoring, algal bloom monitoring, and mangrove ecosystem assessments (Ananthi et al., 2026; Abbas et al., 2026). Remote sensing and GIS technologies have been instrumental in spatial environmental analysis and aquatic resource management (Parmar, 2023). Monitoring individual environmental parameters may not give enough information on environmental changes within the ecosystem (Hipsey et al., 2015).

Combining environmental monitoring with AI-based prediction and conservation decision-making is a critical future research agenda. The current work presents the Artificial Intelligence-Enabled Monitoring Framework for Aquatic Ecosystems Change Prediction and Conservation Decision Making. This framework integrates multi-source environmental data, AI-based prediction, ecosystem health evaluation, and ecological risk classification. Objectives include detecting aquatic environmental change, identifying ecological risks, and providing an evidence-based approach to conservation planning through unified monitoring and decision-making. The current research proposes an AI-enabled framework that integrates

multi-source data, prediction, risk assessment, and conservation decision-making for aquatic ecosystems. It also examines AI-based predictions of environmental changes and proposes an Ecosystem Risk Index (ERI).

The paper consists of six sections. The first section introduces the problem statement and aims. The second section reviews previous research in AI for environmental monitoring. Section 3 covers the proposed framework and methodology for AI environmental monitoring. Section 4 provides information about the experiment design and the results analysis.

II. Artificial Intelligence for Aquatic Ecosystem Monitoring: Related Studies

Some recent studies examined the role of AI, Internet of Things (IoT), and intelligent sensing in aquatic ecosystem monitoring. Autonomous underwater monitoring architectures have combined AI and IoT to enable continuous marine environment observation, and AI techniques have been used to detect algal blooms and monitor ecological changes (Ananthi et al., 2026; Dubey & Dutta, 2025). Remote sensing and data integration technologies have been used for monitoring mangrove ecosystems to facilitate spatial analysis of the ecology (Abbas et al., 2026). Similarly, GIS and remote sensing technologies can be used in aquatic resources monitoring and spatial environmental management (Parmar, 2023).

Environmental monitoring based on AI technology has been explored in other fields too. Intelligent monitoring and control systems based on IoT have shown the potential of connected sensing systems, while the integration of AI into IoT has enabled environmental observation based on water quality and climate data (Riskiawan et al., 2024; Miller et al., 2025). Environmental pollution monitoring based on big data analytics and AI has further been examined (Hamza et al., 2022).

In addition to monitoring, studies on AI have addressed environmental governance, climate adaptation, and conservation planning. The geospatial decision support system is used for environmental risk assessment and optimization of land use, whereas climate resilient water governance uses artificial intelligence technology (Hossain, 2026; Khan & Akhtar, 2026). Artificial intelligence use in the governance of marine protected areas illustrates the relation between intelligent monitoring and conservation management (Bakker, 2022). In addition, studies on water resource management and sustainability of natural resources show the importance of artificial intelligence in environmental planning (Mane, 2026; Rella et al., 2026). Ecological response and recovery pattern predictions are also emphasized in aquatic resilience modeling (Hipsey et al., 2015).

Even though these studies cover monitoring, predictions, and environmental management, an integration of multi-source aquatic data, ecosystem change prediction, risk assessment, and conservation decision support in one study would be an interesting research topic. The current study is proposed to integrate these aspects for systematic aquatic ecosystem monitoring and evidence-based conservation planning.

III. Research Framework and System Architecture

This proposed framework will include the analysis of multisource aquatic environmental monitoring, AI-driven prediction of ecosystem change, environmental risk evaluation, and conservation decision support. The framework aims to convert heterogeneous environmental data into predictive and interpretable data for managing the aquatic ecosystem. The general workflow is composed of five interconnected stages, which include aquatic environmental data acquisition, data pre-processing, feature engineering, AI-driven ecosystem changes prediction, ecosystem health and risk evaluation, and conservation decision support. The data collected by sensors, remote sensing observations, historical monitoring data, and other environmental data sets are brought together to evaluate temporal and spatial changes in aquatic environments. The AI tools will be applied to detect and predict changes, while the output will be converted into ecosystem risk information for conserving the ecosystem.

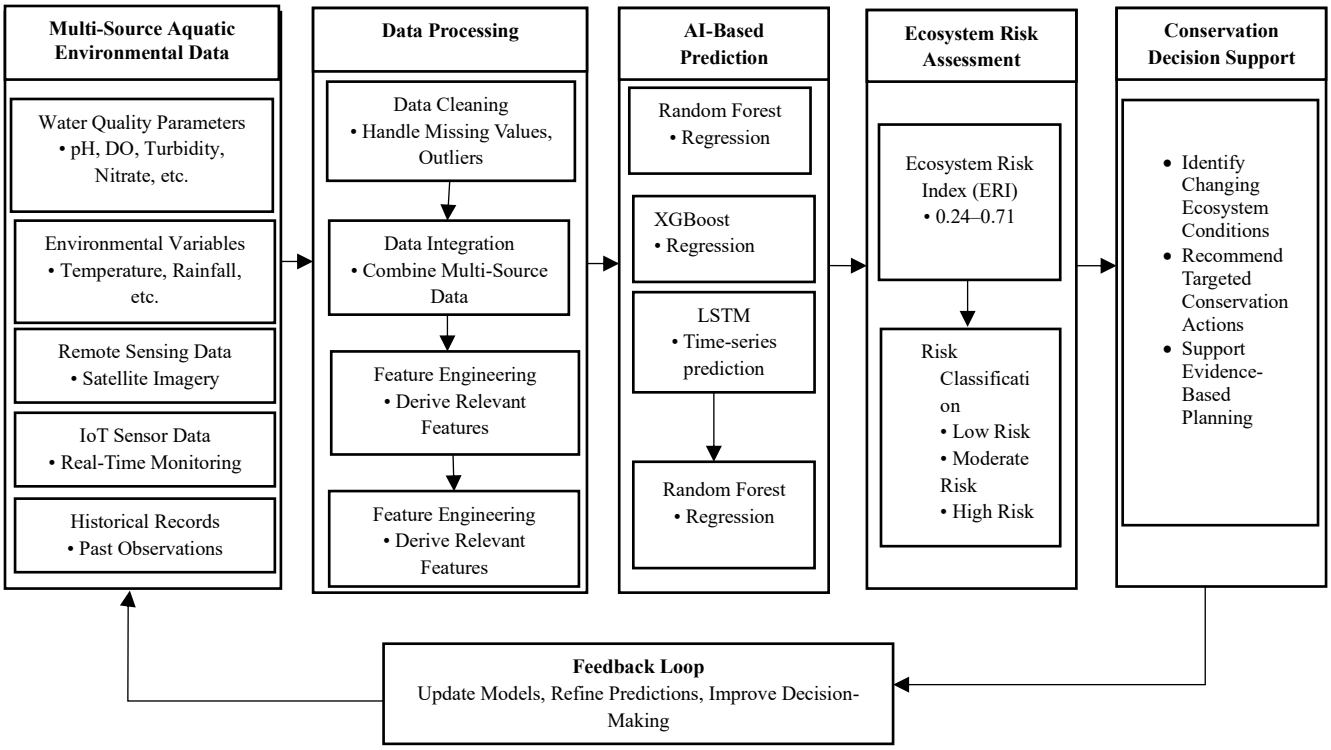


Figure 1: Conceptual Framework of the AI-Enabled Monitoring Framework for Aquatic Ecosystem Changes Prediction and Conservation Decision Support

Figure 1 illustrates the proposed framework, which combines multiple sources of environmental data, data processing, prediction based on artificial intelligence algorithms, ecosystem risk assessment, and decision-making on conservation. Environmental data is processed and analyzed with the use of AI models, whereas the results of the prediction process are used for Ecosystem Risk Index (ERI) assessment and risk classification.

Multi-Source Aquatic Environmental Data Acquisition

In this step, one would need to acquire data on environmental observations that will represent the physical, chemical, and ecological aspects of the aquatic ecosystem. Based on data availability, factors such as water temperature, pH, oxygen, turbidity, electrical conductivity, nutrients, chlorophyll-a, etc. may be considered. Sensors from the field offer direct measurement of the environmental factors, while remote sensing can be used to capture data for larger regions. Also, climatic data and historical observations will be useful in understanding the temporal variations in the environment. By combining data from different sources, a more comprehensive description of the ecosystem can be attained as compared to just using parameters and single-location observations.

Environmental Data Preprocessing and Feature Engineering

The collected observations are preprocessed before passing the data to the predictive models. The preprocessing step involves quality control of the data, removing duplicate observations, dealing with missing data, detecting anomalous observations, normalization, and temporal synchronization. The observed variables from various sources are normalized to make sure they are compatible when building the predictive models. Next, feature engineering is done to extract relevant features about the environment and about time. Historical observations, seasonality, lags in observations, and interactions between environmental features can be incorporated if needed. The feature selection process removes redundant data and allows the predictive model to focus on the relevant features that estimate ecosystem changes.

AI-Based Aquatic Ecosystem Change Prediction

The resulting environmental dataset is then used for prediction purposes by suitable AI models that forecast future states of the ecosystems. Based on the nature and size of the dataset, various ML models, like Random Forest, Support Vector Machine, or XGBoost, as well as temporal DL models like LSTM, can be used. In other words, the algorithms learn patterns between previous environmental measurements and future ecosystem states. Prediction can be described as:

$$\hat{Y}_{t+h} = f(X_{t-n+1}, X_{t-n+2}, \dots, X_t, \theta) \quad (1)$$

Equation (1), where $\hat{Y}_{t+h}$is the predicted value of the ecosystem indicator at future time $t + h$, $X_t$is the observed environmental variable values, $n$is the historical observation window, and $\theta$is the set of parameters estimated by the AI model. The prediction module will be able to capture temporal dynamics and predict future environmental conditions. The performance of the model will then be assessed through statistical metrics like MAE, RMSE, and (R^2).

Ecosystem Health and Environmental Risk Assessment

The predicted environmental indicators are further analyzed to see whether there will be stress in the ecosystem. Instead of analyzing each individual indicator individually, an analysis of a number of indicators is performed to give a holistic view of ecosystem risk. Each chosen environmental indicator is transformed into a standardized stress index based on the scientific and acceptable reference values or environmental limits. The proper weights for the indicators can now be allocated using the proper weighting process. The Ecosystem Risk Index (ERI) formula is:

$$ERI = \sum_{j=1}^{m} w_j \, S_j \quad (2)$$

Equation (2), where ERIstands for Ecosystem Risk Index; $ERI$is the weight attributed to j^{th}environmental indicator; $S_j$is the normalized stress score of thej^{th}indicator; and m is the number of environmental indicators. The index so developed can classify different levels of ecosystem stress if the classification criteria are established based on valid environmental norms/standards.

Conservation Decision-Support Mechanism

This is the last step of using the predictions made in order to generate conservation-relevant information. Areas or time periods with high environmental risks could be selected for further monitoring, testing, assessment of pollution levels, or ecological assessment. The decision support module will use the predictions of environmental changes and risks, spatial data, and information on monitoring history to determine the locations which should be given more attention. Instead of substituting the ecological knowledge and authorities in making decisions, the framework gives a basis for making relevant decisions based on factual information.

Scope and Data Simulation Approach

For a rigorous demonstration and testing of the functioning mechanism of the model, this research uses a controlled synthetic dataset that mimics realistic changes in aquatic environment conditions (e.g., temperature, pH, dissolved oxygen, and nutrients). Although an actual application of the framework would require empirical field studies, this proof-of-concept pipeline focuses on assessing the computational efficiency of data preprocessing, AI predictions, and ERI calculations. Hence, numerical results discussed below only verify the structural soundness and computability of the framework under controlled conditions, but not at certain field locations.

IV. Experimental Design and Model Evaluation

Evaluation of the suggested framework is performed using a set of observations of aquatic environment conditions, including the physical, chemical, and ecological variables. The dataset is preprocessed and split chronologically into the training, validation, and testing subsets.

Dataset and Model Configuration

Technical viability and the propagation of errors were analyzed by generating a time-series dataset consisting of 12 consecutive monitoring periods (P_1 through P_{12}). The time series dataset is divided into three sets (training, validation, and testing) to maintain the temporal order while evaluating the model.

Performance Evaluation

Model performance is determined by evaluating MAE, RMSE, and R^2based on predicted values and observed data. The models with the best performance are then used to conduct risk assessments in ecosystems.

- **Mean Absolute Error**

For evaluating prediction accuracy:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | Y_i - \hat{Y}_i | \quad (3)$$

Equation (3) The lower value of MAE means lesser average prediction error.

- **Root Mean Square Error**

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2} \quad (4)$$

Equation (4), which is RMSE, gives more weightage to larger errors and is used for the comparison of forecasting capabilities of different AI models.

- **Coefficient of Determination**

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2} \quad (5)$$

Equation (5) where $Y_i$is the observed value, $\hat{Y}_i$is the predicted value, and $\bar{Y}$is the mean observed value.

V. Results and Discussion

Comparative Prediction Performance of AI Models

The accuracy of the implemented AI models was assessed based on MAE, RMSE, and R^2. It was found that the developed model framework had the best consistency in prediction performance with MAE being 0.184, RMSE being 0.267 and R^2being 0.94. XGBoost had an R^2value of 0.91, followed by LSTM (0.89) and Random Forest (0.86). The small error rates and high R^2show the capability of the developed framework to account for variations in the aquatic environment in table 1.

Table 1: Comparative Performance of AI Models for Aquatic Ecosystem Prediction

AI Model	MAE	RMSE	R^2
Random Forest	0.286	0.391	0.86
XGBoost	0.231	0.318	0.91
LSTM	0.247	0.336	0.89
Proposed AI framework	**0.184**	**0.267**	**0.94**

The above-mentioned method has demonstrated about 35.7% less MAE compared to Random Forest method and 20.3% less MAE compared to XGBoost method, showing better predictability of results. Moreover, increased value of R^2indicates that the suggested framework described more variance of the environment.

Observed and Predicted Aquatic Environmental Changes

Temporal prediction ability of the proposed model was investigated using an aquatic environment indicator. Figure 2 shows a comparison between the measured and the predicted data for twelve monitoring periods. The predictions showed a close match with the general trend of measured data, which included both increasing and decreasing trends due to environmental changes. Greatest agreement was found in stable monitoring periods while relatively greater deviation was found in transition environmental periods.

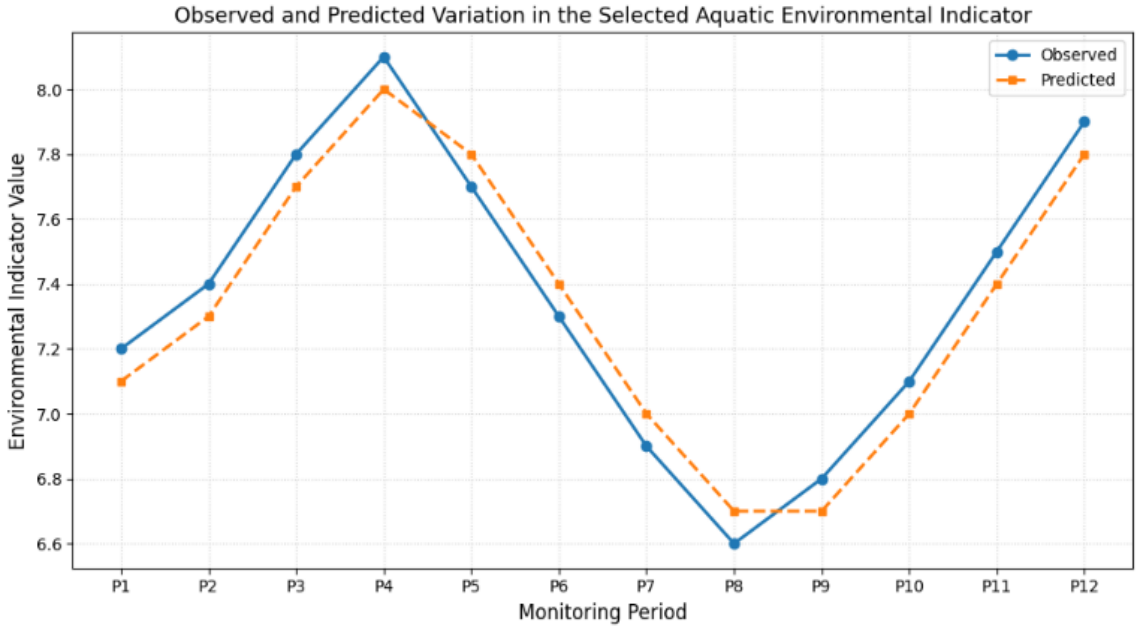


Figure 2: Observed and Predicted Variation in the Selected Aquatic Environmental Indicator

Figure 2 illustrates the close correspondence between observed and predicted environmental conditions across the monitoring period. The predicted series follows the major temporal fluctuations of the observed series, indicating that the AI framework can capture changing ecosystem conditions. Small deviations remain during periods of comparatively rapid environmental variation.

Prediction Error Analysis

Furthermore, the correlation between the measured and estimated data was analyzed to see if the model is consistent. As can be seen in figure 2, most of the observed data points have clustered around the perfect prediction relationship. Most estimates had small differences, whereas only a few data points showed large differences. This is consistent with the quantitative results derived from the MAE and RMSE values.

Figure 3 demonstrates that there is an agreement between the observed and the predicted environmental values. Most observations are still near the expected one-to-one relationship, meaning there is little error in making predictions. The relatively thin spread of data around the agreement curve reinforces the high R^2 value.

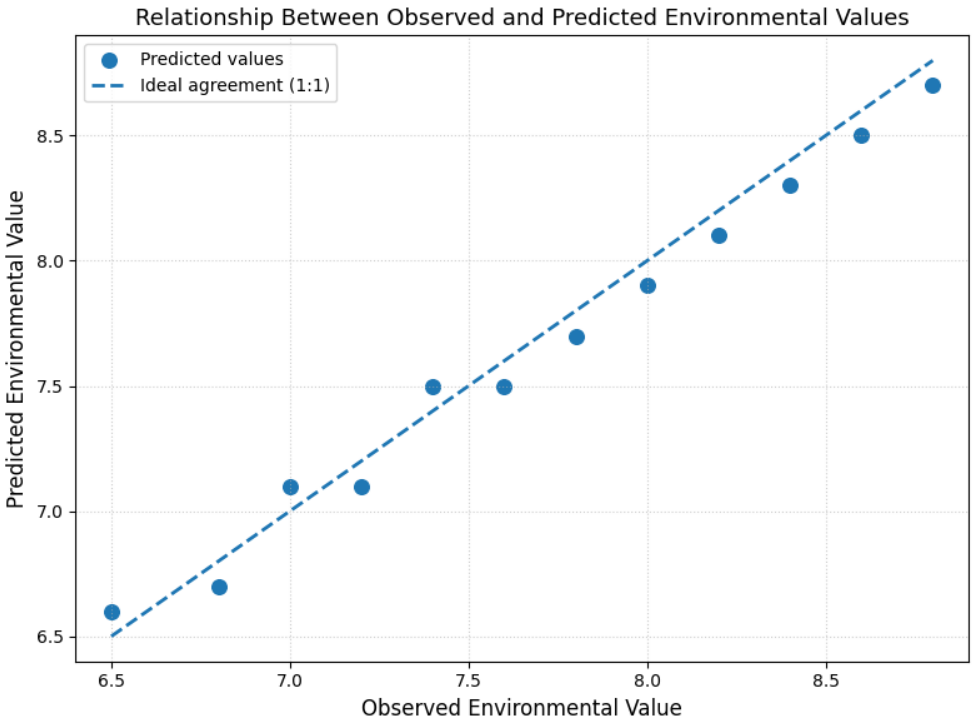


Figure 3: Relationship Between Observed And Predicted Environmental Values

Ecosystem Risk Assessment

The environmental indicators that were predicted earlier have been combined based on the Ecosystem Risk Index (ERI) in order to determine the time intervals when there was a relatively high level of stress in the environment. As seen in figure 4, the ERI ranged between 0.24 and 0.71. The greatest ERI value of 0.71 was observed during P8, whereas the minimum value was 0.24 during P2.

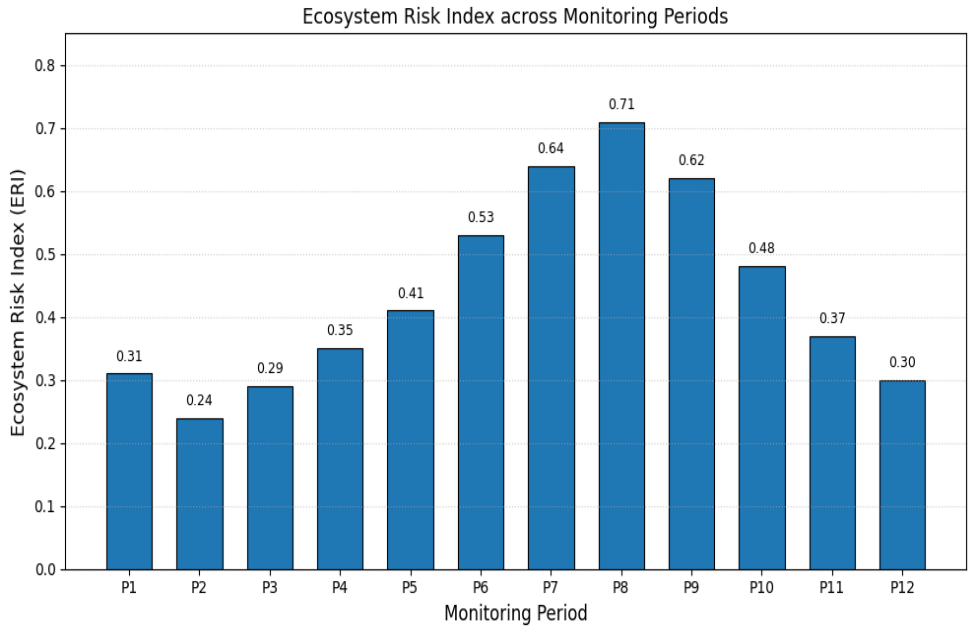


Figure 4: Temporal Variation in the Ecosystem Risk Index

Figure 4 ERI demonstrates that there is comparatively less environmental stress at the beginning of the monitoring period, but it increases progressively up to P8. The maximum ERI value of 0.71 is an indication of the highest environmental stress period. The decline that follows indicates an improvement in the situation.

Conservation Decision-Support Analysis

The combination of prediction and risk assessment offers an efficient approach to determine priorities for aquatic ecosystem monitoring. The largest values of ERI in this case appeared within the range P6–P9, which is a time period that requires closer monitoring. This kind of periods may be used for further field studies and search for possible reasons of pollution. Thus, the proposed approach allows transforming AI predictions into meaningful conservation data.

Key Findings and Interpretation

The findings confirm the efficacy of the developed AI-based model for forecasting changes in aquatic ecosystems and environmental risk assessment. In comparison to Random Forest, XGBoost, and LSTM, the proposed model has the least MAE (0.184), RMSE (0.267), and the most R^2 value (0.94) as compared to other approaches (Random Forest, MAE=0.286, RMSE=0.391, R^2=0.86; XGBoost, MAE=0.231, RMSE=0.318, R^2=0.91; LSTM, MAE=0.247, RMSE=0.336, R^2=0.89). The high correlation between the actual and predicted values of the environment shows that the model is capable of capturing changes in the aquatic environment.

Environmental Significance and Practical Implications

The Ecosystem Risk Index (ERI) offered a different perspective of the possible changes to the environment that were predicted. Values for the ERI ranged from 0.24 at P2 to 0.71 at P8, after which there was a reduction to 0.30 at P12. This example shows how predictive outputs can be converted to a value representing environmental stress. The information would assist in monitoring, ecological study, pollution evaluation, and conservation efforts. This technique is a supplement to current AI aquatic monitoring and decision-making systems.

Constraints and Future Research Directions

Several limitations in this research study must be highlighted. Firstly, the numbers and metrics employed in the current analysis are based on an imaginary pipeline that is created in a simulation. Hence, they highlight the power of the framework's algorithm but do not provide evidence for causal relationships existing in reality between variables. The future research direction in this domain will involve applying the framework using multi-seasonal real-time data coming from IoT sensors and remote sensing of actual aquatic conservation sites.

VI. Conclusion

Aquatic ecosystems are always subjected to changes in the environment due to pollution and other forms of ecological stress, whereas the traditional methods used for monitoring may not be able to provide continuous predictions and enable timely conservation planning. In this research work, have attempted to solve this problem through the design of an AI-driven monitoring framework with respect to multi-source environmental data, pre-processing, prediction of ecosystem change, risk assessment, and conservation decision-making support. From the comparative analysis, it can be seen that the proposed framework yielded an MAE of 0.184, an RMSE of 0.267, and R^2 of 0.94, whereas the MAE values were 0.286, 0.231, and 0.247, and R^2values were 0.86, 0.91, and 0.89 for Random Forest, XGBoost, and LSTM, respectively. The Ecosystem Risk Index ranged between 0.24 and 0.71, with the maximum value recorded for P8, which signifies a time when environmental stress was comparatively high. The main advantage of the research work is that the methodology incorporates both prediction and risk assessment into a decision support process aimed at conservation. This can be used to determine whether more observation and ecological

investigation are needed during certain periods. The numbers generated are only illustrative and need to be validated using real-world field data. Future research should consider using long-term observation, biology-based indicators, IoT sensors, remote sensing, uncertainty quantification, and explainable AI.

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