# Towards Intelligent Aquatic Health Monitoring in Malaysia's Coastal Waters: AI-Driven Harmful Algal Bloom Forecasting with IoT and Cloud Infrastructure

**Article history**

Received:
3 April 2023

Received in revised form:
15 April 2023

Accepted:
25 April 2023

*Corresponding author
amiraatieff@iium.edu.my

Amir 'Aatieff Amir Hussin[1], Ahmad Anwar Zainuddin[2], Nik Nor Muhammad Saifudin Nik Mohd Kamal[3], Normawaty Mohammad-Noor[4], Roziawati Mohd Razali[5], Mohd Nor Azman Ayub[6], Muhammad Farouk Harman[7], Mohd Khairul Azmi Hassan[8], Mohd Izzuddin Mohd Tamrin[9], Krishnan Subramaniam[10], Saidatul Izyanie Kamarudin[11]

*[1, 2, 3, 8 ,9] Kulliyyah of Information and Communication Technology, International Islamic University Malaysia, Malaysia*

*[4] Institute of Oceanography & Maritime Studies, Kulliyyah of Science, International Islamic University Malaysia, Kuantan, Pahang, Malaysia*

*[5, 6, 7] Department of Fisheries, Ministry of Agriculture and Food Industries, Malaysia*

*[10] Mechanical Engineering, School of Engineering (SOE). INTI International College, Penang, Malaysia*

*[11] Fakulti Sains Komputer dan Matematik (FSKM), Universiti Teknologi Mara (UiTM), Shah Alam, Selangor, Malaysia*

*[1]amiraatieff@iium.edu.my, [2]anwarzain@iium.edu.my, [3]saifudinkamal11@gmail.com, [4]normahwaty@iium.edu.my, [5]roziawati@dof.gov.my, [6]nor_azman@dof.gov.my, [7]mhd.farouk@dof.gov.my, [8]mkazmi@iium.edu.my, [9]izzuddin@iium.edu.my, m[10]krishnan.subramaniam@newinti.edu.my, [11]saidatulizyanie@uitm.edu.my*

## *Abstract*

*Harmful Algal Blooms (HABs) pose significant threats to aquaculture, marine ecosystems, and coastal economies, requiring timely and reliable monitoring approaches for early detection and response. Conventional water quality monitoring methods are often limited by high operational cost, delayed data acquisition, and insufficient forecasting capability for dynamic coastal environments. This study presents an integrated intelligent aquatic health monitoring system that combines Internet of Things (IoT)-based water quality sensing, cloud-based real-time data management, and artificial intelligence (AI) models for HAB monitoring in Malaysian coastal waters. The proposed system employs multi-parameter sensors connected through ESP32 microcontrollers for continuous monitoring of key water quality indicators, with data transmission via MQTT to a cloud dashboard*

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* *Corresponding author. amiraatieff@iium.edu.my*

*for visualisation and remote access. Field validation was conducted at Sungai Geting, Kelantan, by comparing prototype sensor readings against benchmark YSI ProDSS measurements. Two AI models, namely an Adjusted Combined Model (ACM) integrating Radial Basis Function Networks (RBFN) and Fuzzy C-Means clustering, and Long Short-Term Memory (LSTM), were evaluated for chlorophyll-a forecasting and HAB prediction. Experimental results showed that ACM achieved superior short-term predictive performance with lower RMSE and MAE, while LSTM demonstrated competitive performance for temporal sequence modelling. The findings demonstrate the potential of integrating IoT and AI to support cost-effective, real-time, and predictive HAB monitoring for sustainable aquaculture management and coastal environmental surveillance.*

***Keywords:*** *Harmful Algal Bloom, IoT AI Forecasting, Water Quality Monitoring, Real-time Detection, Intelligent Data Analytics.*

## 1. Introduction

Harmful Algal Blooms (HABs) are a growing environmental concern in coastal and aquaculture ecosystems due to their adverse impacts on marine biodiversity, water quality, fisheries, and public health [1], [2]. HAB events occur when certain algae species grows rapidly under favourable environmental conditions, often producing toxins or causing oxygen depletion that can lead to fish mortality, ecosystem imbalance, and significant economic losses to aquaculture industries [3], [4]. In Malaysia, several HAB incidents have been reported, particularly in Perak, Penang, and Kelantan, highlighting the need for timely monitoring and predictive management strategies to reduce ecological and socioeconomic impacts [1]. Fig. 1 illustrates the distribution of current speed and reported HAB cases along the east coast of Peninsular Malaysia, highlighting environmentally sensitive coastal areas with aquaculture activities and mangrove ecosystems.

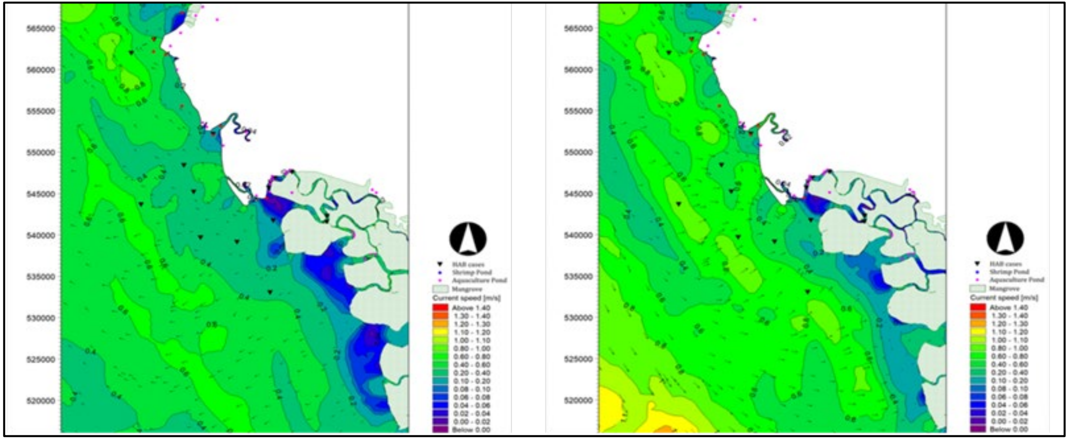


**Figure 1. Distribution of Current Speed and Reported HAB Cases Along the East Coast of Peninsular Malaysia.**

Conventional HAB monitoring typically relies on periodic field sampling and laboratory-based water quality analysis [5]. Although these approaches provide reliable measurements, they are often labour-intensive, costly, and unable to provide continuous real-time monitoring. Such limitations reduce the ability of authorities and aquaculture operators to detect rapid environmental changes and respond proactively before bloom events become severe [1]. Recent advances in Internet of Things (IoT) technology have introduced cost-effective alternatives through real-time water quality monitoring using distributed sensors, wireless communication, and cloud-based dashboards [6], [7]. Multi-parameter sensing systems capable of continuously measuring temperature, dissolved oxygen, salinity, pH, turbidity, and chlorophyll-a have shown significant potential for improving aquatic environmental monitoring [8], [9].

Beyond real-time sensing, Artificial Intelligence (AI) has emerged as an important tool for forecasting water quality trends and predicting HAB occurrence [10]. Machine learning and deep learning techniques such as Radial Basis Function Networks (RBFN), clustering-based models, Long Short-Term Memory (LSTM), and ensemble learning approaches have demonstrated promising predictive performance in modelling nonlinear environmental behaviour and temporal water quality variations [11]. However, many existing studies focus primarily on either sensor-based monitoring or predictive modelling as separate components, with limited sensor integration, cloud-based data management, and AI-driven forecasting into a unified operational framework for HAB monitoring [12], [13].

Furthermore, practical deployment challenges remain significant in low-cost aquatic monitoring systems, particularly in terms of sensor reliability, cloud connectivity, and predictive performance under real environmental conditions [7], [10]. These limitations highlight the need for integrated intelligent monitoring platforms that combine continuous sensing, remote visualisation, and predictive analytics to support early warning and decision-making in aquaculture environments [10]. Beyond that, HABs also present significant socio-economic challenges by affecting food security, aquaculture productivity, and coastal economic activities [14]. In Malaysia, the emphasis on sustainable aquaculture and environmental resilience under national development initiatives highlights the importance of reliable monitoring and early warning systems. HAB events can result in substantial economic losses due to fish mortality, shellfish toxicity, and disruptions to aquaculture operations [1], [10].

This study presents an intelligent aquatic health monitoring system for Malaysian coastal waters by integrating IoT-based real-time water quality sensing, cloud-based monitoring, and AI-driven HAB prediction within a unified framework. To enhance predictive capability, two AI models, namely an Adjusted Combined Model (ACM) which integrates RBFN and Fuzzy C-Means clustering, and LSTM, were evaluated for chlorophyll-a forecasting and HAB prediction. The main contributions of this work: (1) development of an integrated AIoT-based aquatic monitoring architecture for continuous environmental surveillance, (2) field validation of a low-cost real-time water quality sensing platform in Malaysian coastal waters, and (3) comparative evaluation of hybrid and deep learning models for predictive HAB monitoring. The remainder of this paper is organized as follows. Section 2 presents the literature review on HAB monitoring, IoT-based aquatic sensing, and AI-driven predictive approaches. Section 3 describes the methodology, including system architecture, sensor deployment, and AI modelling techniques. Section 4 presents the experimental results and discussion. Finally, Section 5 concludes the study and outlines future work.

## 2. Literature Review

HABs monitoring requires an interdisciplinary approach that combines environmental science, sensing technologies, and predictive analytics [7], [10]. Previous studies have highlighted the strong relationship between HAB development and key water quality parameters such as temperature, dissolved oxygen, salinity, pH, turbidity, nutrient concentrations, and chlorophyll-a, which is widely used as a proxy indicator of algal biomass [15], [16]. At the same time, advances in IoT, cloud computing, and AI have expanded the potential for real-time monitoring and predictive forecasting of HAB events [14]. This section reviews existing studies in HAB-related water quality monitoring, IoT-enabled aquatic sensing systems, and AI-driven predictive approaches that form the scientific and technological basis of this work.

### 2.1. HAB Monitoring and Water Quality Indicators

HABs occur when algae proliferate rapidly under favourable environmental conditions, often producing toxins or causing oxygen depletion that disrupt aquatic ecosystems and threaten fisheries and aquaculture activities [15]. HAB events are influenced by multiple environmental and chemical factors, making water quality monitoring an important component in bloom detection and early warning systems. In coastal environments, changing physical and chemical conditions can alter algal growth dynamics, species dominance, and bloom severity [1].

Several water quality parameters have been identified as important indicators of HAB formation. Water temperature influences algal metabolic activity and growth rates, while dissolved oxygen levels often decline during bloom decomposition, resulting in hypoxic conditions harmful to aquatic organisms [17]. Salinity, pH, turbidity, and oxidation-reduction potential (ORP) also affect bloom dynamics by influencing species composition and aquatic chemical balance [18], [19]. Among these parameters, chlorophyll-a is widely used as a proxy indicator of algal biomass and remains central to HAB monitoring strategies, while nutrient enrichment such as nitrate and phosphate contributes to eutrophication and increased bloom frequency in coastal waters [10], [18].

### 2.2. IoT-Based Aquatic Monitoring Systems

Recent developments in low-cost sensor technologies and IoT-based monitoring systems have improved the feasibility of continuous water quality surveillance in aquatic environments [20]. While commercial multiparameter instruments such as YSI ProDSS provide highly reliable measurements, their cost and maintenance requirements limit large-scale deployment [21]. In contrast, low-cost sensor platforms offer scalable alternatives but often face challenges related to calibration stability, measurement accuracy, biofouling, and long-term field reliability [22].

The integration of IoT technologies through microcontrollers, wireless communication protocols, and cloud platforms has enabled real-time acquisition, transmission, storage, and visualisation of water quality data [10], [20]. Platforms such as Microsoft Azure [23], [24] and ThingsBoard [10] support remote monitoring, historical trend analysis, and early warning alerts through cloud-based dashboards and rule-based automation. These systems improve situational awareness by allowing continuous observation of environmental parameters and supporting timely decision-making in aquaculture and coastal management applications. However, practical deployment challenges remain in ensuring sensor robustness, communication stability, and cost-effective scalability under real environmental conditions.

### 2.3. AI Approaches for HAB Prediction and Research Gap

Artificial Intelligence (AI) has emerged as an important tool for forecasting HAB events by analysing historical water quality patterns and identifying nonlinear relationships associated with bloom formation [8], [12]. Machine learning approaches such as RBFN [25] have demonstrated strong performance in modelling nonlinear environmental systems and short-term predictive tasks, while fuzzy clustering methods improve interpretability by classifying water quality conditions into bloom risk categories [25], [26]. Hybrid approaches combining neural networks and fuzzy logic have shown promising results in improving predictive accuracy for complex ecological systems. In addition, deep learning architectures such as LSTM and ensemble learning models have demonstrated strong capability in modelling temporal and spatiotemporal HAB dynamics for long-term forecasting [27].

Despite these advances, many previous studies focus primarily on sensor-based monitoring or predictive modelling as separate components, with limited integration of low-cost sensing, IoT-cloud infrastructure, field validation, and embedded AI forecasting within a unified operational HAB monitoring framework [20]. These limitations highlight the need for integrated AIoT-based systems capable of supporting continuous monitoring, predictive analytics, and real-time early warning for practical aquaculture and coastal environmental management. This study addresses this gap by integrating a low-cost multi-parameter sensing platform, cloud-based monitoring infrastructure, and two predictive AI models, namely the ACM and LSTM, into a unified HAB detection and forecasting framework for Malaysian coastal waters.

## 3. Methodology

This study adopted a unified methodology that integrates IoT-based water quality monitoring, field validation, and AI forecasting for HAB detection. The framework consists of three main stages: system development for real-time data acquisition and cloud-based monitoring, field deployment for sensor validation against benchmark instruments, and AI modelling for chlorophyll-a forecasting as an indicator of HAB risk. This dual approach evaluates both the feasibility of low-cost IoT monitoring systems and the predictive capability of AI-driven environmental forecasting.

### 3.1. System Architecture and Design

The proposed HAB detection system was developed as a modular IoT framework consisting of a data acquisition layer and a visualisation-analysis layer, as illustrated in Fig. 2. At the acquisition layer, prototype multiparameter sensors were interfaced with an ESP32 microcontroller for on-site data collection, preprocessing, and wireless transmission. Sensor data were transmitted using the MQTT protocol to a cloud-based infrastructure.

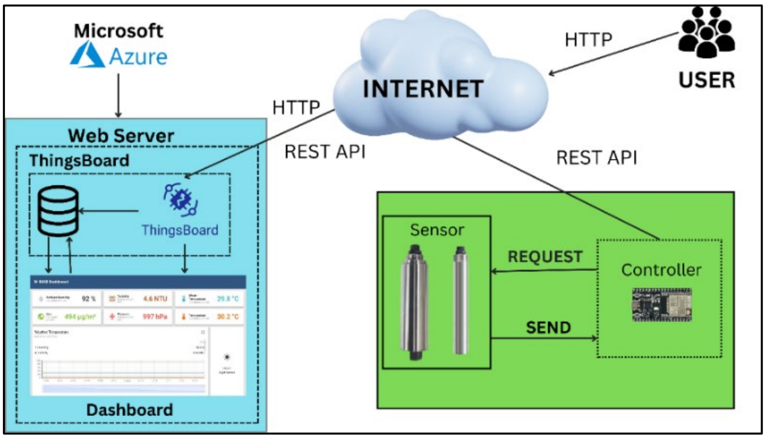


**Figure 2. System Architecture of the IoT-Enabled HAB Detection System**

At the visualisation-analysis layer, ThingsBoard was deployed for real-time dashboard monitoring, while Microsoft Azure provided backend support for data storage, long-term analytics, and AI model integration. This architecture enabled continuous interaction between field sensors, cloud processing, and end-user monitoring for real-time HAB surveillance.

### 3.2. Sensor Deployment and Data Acquisition

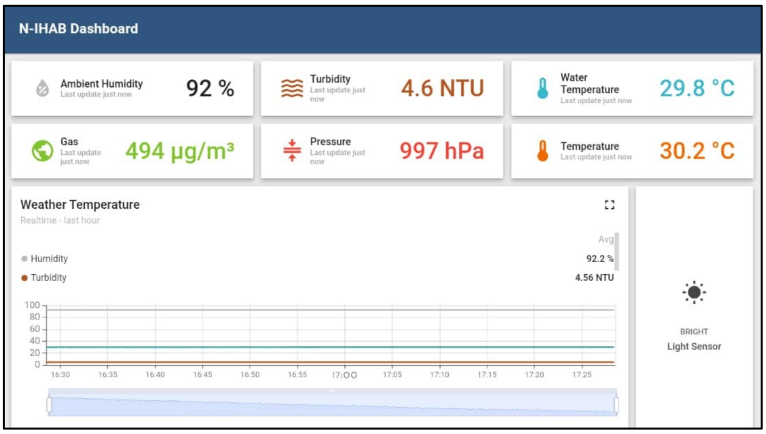
Two categories of sensors were employed: prototype sensors as the experimental devices and YSI ProDSS multiparameter sondes as benchmark instruments. Both systems measured key water quality parameters including water temperature, dissolved oxygen (DO), salinity, and chlorophyll-a concentration, as summarized in Table 1.

**Table 1. Summary of Sensors Employed in the Experiment**

| Sensor Type | Parameters Measured | Strengths | Limitations |
|---|---|---|---|
| Prototype (Experimental Device) | Water Temperature,<br>Dissolved Oxygen,<br>Salinity,<br>Chlorophyll-a | Low-cost, lightweight, real-time monitoring, modular design | Calibration drift, sensitivity to biofouling, hardware stability issues |
| YSI ProDSS (Benchmark) | pH,<br>Water Temperature,<br>Dissolved Oxygen,<br>Salinity,<br>Chlorophyll-a,<br>Total Dissolved | High accuracy, robust field performance, widely validated | Expensive, frequent calibration required, not scalable for large deployments |

| | | | |
|---|---|---|---|
| | Solids,<br>Submerged Depth | | |

Field deployment was conducted at Sungai Geting, Kelantan, a coastal site reported to be experiencing a red tide event during the study period [17]. Measurements were collected simultaneously from both systems at five-minute intervals across multiple sampling points to enable direct comparison under real environmental conditions. Sensor readings were transmitted through the IoT pipeline for real-time visualisation and cloud-based storage, as shown in Fig. 3.



N-IHAB Dashboard

Ambient Humidity 92 % Last update just now

Turbidity 4.6 NTU Last update just now

Water Temperature 29.8 °C Last update just now

Gas 494 µg/m³ Last update just now

Pressure 997 hPa Last update just now

Temperature 30.2 °C Last update just now

Weather Temperature

Realtime - last hour

| | Avg |
|---|---|
| Humidity | 92.2 % |
| Turbidity | 4.56 NTU |

BRIGHT

Light Sensor

**Figure 3. ThingsBoard Dashboard Displaying Real-Time Water Quality Parameters**

Historical and field-acquired datasets were archived in Microsoft Azure and used for subsequent trend analysis and AI-based forecasting. To evaluate prototype sensor performance, benchmark comparisons were conducted using statistical error metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), bias, and correlation analysis.

### 3.3. Artificial Intelligence Modelling

AI modelling was conducted using historical water quality data from May 2024 to January 2025, supplemented with field measurements from Sungai Geting. Chlorophyll-a concentration was selected as the forecasting target due to its role as a proxy indicator for HAB risk. Data preprocessing included anomaly filtering, missing value imputation, smoothing, normalisation, and temporal train-test splitting (70:30) to preserve chronological integrity.

Two predictive modelling approaches were evaluated. The first was ACM, which RBFN with Fuzzy C-Means clustering. RBFN was used to model nonlinear relationships between water quality variables and chlorophyll-a behaviour, while fuzzy clustering classified bloom risk levels into interpretable categories. The ACM combined both approaches to improve predictive accuracy and decision support capability.

The second approach employed a LSTM neural network to model temporal dependencies in chlorophyll-a time-series data for longer-term forecasting.

Prediction outputs from both models were integrated into the dashboard for real-time visualisation of forecasted HAB risk, as illustrated in Fig. 4.

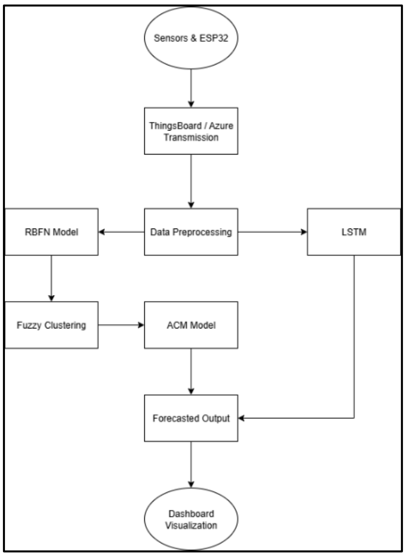


**Figure 4. Workflow of the AI-based Forecasting Pipeline**

### 3.4. Evaluation Metrics

System evaluation was conducted in two dimensions: sensor performance and AI predictive performance.

a. For sensor validation, prototype measurements were compared against YSI ProDSS benchmark readings for water temperature, dissolved oxygen (DO), salinity, and chlorophyll-a concentration. Evaluation metrics included bias, RMSE, MAE, and correlation analysis to quantify measurement agreement and sensor reliability.

a. For AI predictive performance, the ACM and LSTM models were evaluated using RMSE and MAE for chlorophyll-a forecasting, together with classification accuracy for HAB risk categorization. These evaluation metrics were used to assess predictive performance in terms of forecasting precision, temporal modelling capability, and suitability for HAB early warning applications.

## 4. Results and Discussion

This section presents the results of system implementation, field validation, and AI-based forecasting for HAB monitoring. The findings address two objectives: (i) evaluation of low-cost IoT sensors against a commercial reference instrument, and (ii) assessment of AI models for short- and long-term chlorophyll-a forecasting. The discussion is structured into sensor performance, system performance, forecasting results, and implications.

### 4.1. Sensor Evaluation

Field deployment at Sungai Geting compared prototype sensors with the YSI ProDSS across temperature, dissolved oxygen (DO), salinity, and chlorophyll-a measurements. As summarised in Table 2, temperature showed strong agreement with minimal deviation, while salinity followed similar trends with minor overestimation under variable tidal conditions.

**Table 2. Comparative Water Quality Measurements Obtained from Prototype Sensors and YSI ProDSS Benchmarks at Sungai Geting**

| Parameter | Prototype Sensor (Mean ± SD) | YSI ProDSS (Mean ± SD) | Difference / Bias | Remarks |
|---|---|---|---|---|
| Temperature (°C) | 28.6 ± 0.3 | 28.4 ± 0.2 | +0.2 | Good agreement |
| Dissolved Oxygen (mg/L) | 5.8 ± 0.6 | 6.4 ± 0.4 | -0.6 | Underestimation at low DO |
| Salinity (ppt) | 31.5 ± 1.2 | 30.0 ± 0.8 | +1.5 | Calibration drift observed |
| Chlorophyll-a (µg/L) | 18.4 ± 3.2 | 14.1 ± 2.5 | +4.3 | Overestimation during bloom |

Larger discrepancies were observed in DO and chlorophyll-a, with the prototype underestimating low DO levels and overestimating chlorophyll-a during bloom decline. These errors are attributed to calibration drift, biofouling, and sensor sensitivity under estuarine variability.

Despite these limitations, the prototype captured overall temporal patterns consistent with the reference system. Continuous 10-minute sampling further demonstrates suitability for high-frequency monitoring. Results indicate that low-cost sensors can support scalable HAB monitoring when complemented with improved calibration and anti-fouling strategies.

### 4.2. IoT and AI Forecasting

The IoT system, implemented using ESP32 and ThingsBoard with Azure integration, enabled real-time monitoring and historical data storage. The dashboard supported continuous visualisation and threshold-based alerts. System uptime reached approximately 95%, with latency between 2–5 seconds under normal conditions. Data loss remained below 2%, mainly due to intermittent network connectivity and limited buffering capacity during high-frequency sampling. Overall, the results confirm the feasibility of a hybrid IoT–cloud architecture for near real-time coastal monitoring, with performance primarily constrained by communication reliability rather than processing capability.

To extend the system beyond real-time monitoring, AI-based forecasting models were developed using historical chlorophyll-a data as a proxy for HAB risk. Two modelling approaches were evaluated: an ACM, and a LSTM neural network. Table 3 shows the performance comparison between these models.

**Table 3. Performance comparison of forecasting models**

| Model | RMSE (µg/L) | MAE (µg/L) | Accuracy (%) | Application |
|---|---|---|---|---|
| Radial Basis Function Networks (RBFN) | 2.85 | 2.10 | - | Short-term regression (sudden changes) |
| Fuzzy Clustering (FC) | - | - | 78.6 | Risk classification (low/med/high) |
| Adjusted Combined Model (RBFN + FCM) | 2.40 | 1.95 | 85.2 | Short-term prediction & decision support |
| Long Short-Term Memory (LSTM) | 2.65 | 2.05 | 83.1 | Long-term forecasting (trend analysis) |

The ACM performed better in short-term forecasting, capturing abrupt bloom dynamics with lower error and higher interpretability. The LSTM showed stronger performance in long-term trend modelling due to its ability to capture temporal dependencies. Overall, results indicate that ACM is more suitable for early warning applications requiring rapid response, while LSTM is better suited for longer-horizon forecasting. This suggests that HAB prediction benefits from multi-model or horizon-dependent approaches rather than a single unified model.

### 4.4. Implications and Discussion

The results demonstrate that low-cost IoT sensors can reproduce key temporal dynamics of water quality parameters despite reduced absolute accuracy, enabling dense and continuous monitoring networks for HAB detection.

Sensor limitations in chlorophyll-a and DO highlight persistent challenges related to biofouling and calibration drift, suggesting that future systems should integrate adaptive or model-assisted correction mechanisms rather than relying solely on hardware improvements. The IoT–cloud system confirms the feasibility of real-time environmental monitoring using embedded devices, though performance is primarily limited by network stability and buffering constraints rather than computation.

From a modelling perspective, ACM and LSTM exhibit complementary strengths across forecasting horizons, reinforcing the need for hybrid or hierarchical modelling strategies in HAB prediction systems. Overall, the study demonstrates the viability of an end-to-end cyber-physical framework combining low-cost sensing, cloud connectivity, and AI forecasting for HAB monitoring. Operational constraints remain dominated by environmental fouling, calibration stability, and communication reliability.

## 5. Conclusion

This study developed and validated an IoT-based system for HAB monitoring and forecasting by integrating low-cost sensors with ThingsBoard and Microsoft Azure for real-time data acquisition and cloud storage. Field deployment at Sungai Geting demonstrated that the prototype sensors can capture key water quality dynamics, though performance is limited by calibration drift and biofouling. AI forecasting using chlorophyll-a showed that the ACM is more effective for short-term prediction, while LSTM performs better for long-term trend modelling, highlighting the importance of horizon-dependent forecasting strategies. The integration of IoT and AI confirms the feasibility of transitioning from reactive monitoring to proactive HAB prediction. Overall, the system demonstrates the potential of low-cost, data-driven approaches for scalable coastal monitoring, while remaining constrained by sensor stability and communication reliability. Future work should focus on improving sensor durability, expanding datasets across full bloom cycles, and enhancing system robustness for continuous deployment.

## Acknowledgments

This research was supported by the Department of Fisheries (DOF), Malaysia under the 12th Malaysia Plan Development Fund (Project Code: 22501-509) and Ministry of Higher Education of Malaysia (MOHE) under Fundamental research Grant Scheme (FRGS/1/2024/ICT02/UIAM/02/4), project ID FRGS24-327-0936. The authors would like to express their gratitude to the Kulliyyah of Information and Communication Technology (KICT) and Institute of Oceanography and Maritime Studies (INOCEM) of International Islamic University Malaysia (IIUM) for their collaboration and participation in this study.

### Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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