

# AN IoT-BASED REAL-TIME WATER QUALITY MONITORING SYSTEM FOR INTEGRATED RICE-SHRIMP FARMING IN THE MEKONG DELTA

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**Abstract** - This study designed, implemented, and field-evaluated a low-cost Internet of Things (IoT)-based system for real-time water quality monitoring in integrated rice-black tiger shrimp farming at Xeo Dinh Hamlet, Tay Yen Commune, An Giang Province. The system used two ESP32-C5 microcontrollers, DFRobot Gravity sensors for pH, dissolved oxygen (DO), and electrical conductivity (EC), a DS18B20 temperature sensor, and an OLED display housed in an IP65 enclosure. Data were transmitted via Wi-Fi to a MySQL database every 5 minutes, with a web dashboard and email alerts. During 69 days of deployment from 1 February to 10 April 2026, the system achieved a 98.2% data collection rate with 19,519 valid samples, capturing clear diurnal cycles, a dry-season increasing trend, and a mid-March salinity intrusion event with timely alerts. The hardware cost was approximately 10.9 million VND, supporting replication by small-scale farming households.

**Key words** - Internet of Things; water quality monitoring; rice-shrimp farming; Mekong Delta; ESP32

## 1. Introduction

The Mekong Delta is one of the key agricultural and aquaculture production regions of Southeast Asia, contributing approximately 50% of Vietnam's rice output and more than 65% of the country's farmed aquatic production [1, 2]. Among sustainable farming systems adapted to climate change, the integrated rice-black tiger shrimp farming system has emerged as an important livelihood strategy in coastal provinces, particularly in the border area of the former Kien Giang Province, which was merged into An Giang Province under the 2025 administrative reform. In this system, farmers rotate rice cultivation during the rainy season, when freshwater is abundant, with black tiger shrimp farming, *Penaeus monodon*, during the dry season, when water becomes saline under tidal influence [1, 2].

However, climate change, sea-level rise, and increasing salinity intrusion are seriously threatening the sustainability of this farming system [3, 4]. Several studies have indicated that the ground elevation of the Mekong Delta is much lower than previously estimated, making the region even more vulnerable to sea-level rise [5]. Salinity intrusion events and abnormal environmental fluctuations in recent years have caused considerable losses in shrimp productivity across many coastal areas [3, 4]. Key water quality parameters - including salinity, pH, dissolved oxygen (DO), temperature, and ammonium ( $\text{NH}_4^+$ ) - must remain within relatively narrow permissible ranges, and sudden threshold-exceeding fluctuations can cause mass shrimp mortality within only a few hours [6].

In the context of the Mekong Delta, nocturnal oxygen depletion and abnormal salinity intrusion are two leading causes of losses for shrimp farmers [4, 6, 7]. The ability to provide early prediction of these events, based on high-density monitoring data, is a prerequisite for shifting from reactive management to proactive management - intervening before dangerous thresholds are exceeded. This constitutes the scientific motivation of the present study.

In brackish-water black tiger shrimp farming, dissolved oxygen is the most critical parameter: the recommended safe threshold is above 4 mg/L, while prolonged DO levels below 2 mg/L can cause stress, reduced growth, and mass mortality [6]. Salinity, inferred from EC, governs osmotic pressure and the molting process of shrimp, whereas pH and temperature affect ammonium toxicity and metabolic rate. Because these parameters vary strongly according to diurnal, seasonal, and tidal cycles, continuous high-frequency monitoring is essential for effective risk management.

At present, most farmers still rely on handheld meters or chemical test kits, which provide information only at specific points in time and may miss rapid fluctuations preceding adverse events [8]. Internet of Things (IoT) technology has created opportunities for low-cost environmental monitoring systems that operate continuously and in real time [9, 10, 11]. Many international studies have applied IoT in aquaculture, including wireless monitoring of fish ponds [12], an ESP32-based multisensor system measuring temperature, pH, DO, and EC [13], open-source hardware for precision aquaculture [14], accuracy improvement of low-cost sensors using linear regression [15], and integration of IoT with artificial intelligence-based surrogate models for smart farm management [16]. Recent reviews [11, 17] have also confirmed the trend of shifting from expensive sensors to low-cost solutions based on embedded microcontrollers, together with the need to standardize calibration procedures and data quality control.

In Vietnam, Huynh et al. demonstrated the effectiveness of an IoT architecture integrating multiparameter sensors with real-time automated control through a smart greenhouse system using a closed-loop control mechanism to optimize crop growth conditions [18]. In particular, Danh et al. designed and deployed an IoT-based water quality monitoring system for aquaculture in the Mekong Delta [19], demonstrating the practical application potential of this technology under local

conditions. Several related domestic studies have also been published. Phat [20] proposed a wireless sensor network model for monitoring temperature, pH, dissolved oxygen, and salinity parameters in support of whiteleg shrimp farming, while Thanh [21] developed an IoT system for real-time monitoring and warning of water pollution levels using a wireless sensor network, web-based visualization, and SMS and email alerts.

However, studies specifically designed for integrated rice–black tiger shrimp farming systems, with costs suitable for small-scale farming households and validated through long-term field deployment, remain limited. Compared with previously published systems using the same group of common components, such as ESP32 microcontrollers, DFRobot Gravity sensors, MySQL databases, web dashboards, and email alerts, the contribution of this study does not lie in the invention of new components but in three specific aspects. First, it proposes a two-microcontroller hardware architecture that separates sensor signal acquisition from Wi-Fi communication, thereby reducing real-time conflicts and improving stability compared with the single-microcontroller architecture commonly used in previous studies by Chen et al. [12], Lin et al. [13], and Jais et al. [15]. Second, the system was deployed continuously in the field for 69 days at a sampling interval of 5 minutes, which is considerably longer than the studies by Chen et al. [12] and Jais et al. [15], which were often limited to laboratory or tank-scale conditions over periods ranging from several days to a few weeks; this deployment was combined with periodic quantitative validation using reference devices throughout the operation period. Third, this is one of the few systems designed and validated through long-term field deployment specifically for the brackish-water rotational integrated rice–black tiger shrimp farming system in the Mekong Delta, in contrast to previous domestic studies that focused on intensive shrimp ponds [20] or general water pollution monitoring [21].

This paper aims to present the design, assembly, and field deployment of a complete IoT system at an integrated rice–black tiger shrimp pond in Tay Yen Commune, An Giang Province. The main contributions are as follows: (1) designing and fabricating a low-cost IoT system using readily available common components, suitable for replication by small-scale farming households; (2) establishing a long-term field monitoring dataset for four water quality parameters, together with an automated data quality control procedure; and (3) analyzing and evaluating the collected data as a basis for smart shrimp pond management and the development of predictive models for abnormal events.

## 2. System design and deployment

### 2.1. Study area and monitoring requirements

The monitoring station was installed in a brackish-water black tiger shrimp pond under an integrated rice–shrimp farming system in Xeo Dinh Hamlet, Tay Yen Commune, An Giang Province, Vietnam, at approximately 9°54' N and 105°02' E. The site is located

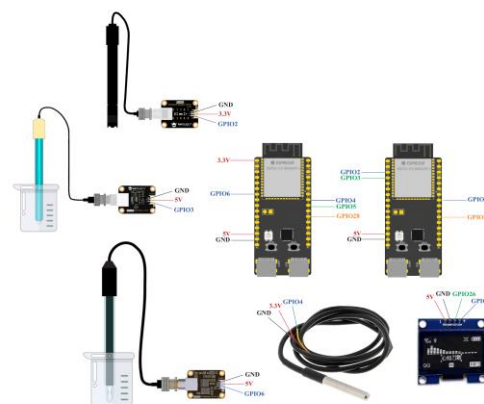
in the coastal zone of the Mekong Delta, where the canal network is affected by tides during the dry season, from December to May.

The pond covers an area of approximately 20 ha, with a large open water surface and a water depth ranging from 1.2 to 1.5 m. The pond is equipped with an electrically driven pump operating according to the Bernoulli principle, specifically the Venturi effect, to entrain air into the water flow in order to increase dissolved oxygen. The water is then distributed to multiple points across the pond surface to generate circulation. This mechanism is combined with strong and continuous winds over the open field area, which disturb the surface water layer and promote oxygen replenishment from the atmosphere. Together, these two mechanisms help limit stratification and maintain relatively stable dissolved oxygen levels in the pond.

Based on farmer consultation and the relevant literature [6], four parameters were selected for continuous monitoring at 5-minute intervals: temperature, with an optimal range of 26–32°C; pH, from 7.5 to 8.5; DO, greater than 4 mg/L; and electrical conductivity, EC, corresponding to a salinity range of 10–25 ppt.  $\text{NH}_4^+$  was measured manually on a weekly basis using a Sera test kit, as the cost of automatic measurement equipment exceeded the project budget.

### 2.2. Hardware design

The hardware was designed to simultaneously satisfy four criteria: low cost for replication by small-scale farming households; low power consumption and stable operation over multiple weeks, suitable for power supply conditions in rural coastal areas; resistance to humid, corrosive brackish-water environments; and modularity to facilitate replacement, cleaning, and calibration of individual sensors. On this basis, the overall hardware connection diagram is presented in Figure 1.



**Figure 1.** Hardware connection diagram of the IoT water quality monitoring system

Figure 1 illustrates the complete hardware wiring diagram, in which the wire colors and corresponding GPIO labels show the connections among each sensor, the two ESP32-C5 microcontrollers, and the OLED display. The system uses two WeAct ESP32-C5 microcontrollers in a functionally separated architecture consisting of a sensor node and a communication node, as shown in Figure 1.

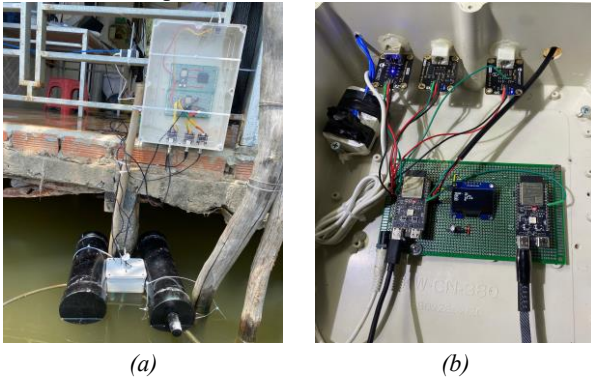
The sensor node is responsible for reading the DO sensor through GPIO2, the pH sensor through GPIO3, the EC sensor through GPIO6, and the DS18B20 temperature sensor through GPIO4 via analog and 1-wire interfaces. It also displays instantaneous values on a 1.3-inch OLED display via the I2C interface, using GPIO25 and GPIO26. The data are then transmitted via UART, using GPIO5 and GPIO28, to the communication node. The communication node manages the Wi-Fi connection and sends data by HTTP POST directly to the MySQL server through a PHP endpoint.

The DFRobot Gravity sensors for pH, EC, and DO have accuracies of  $\pm 0.1$ ,  $\pm 5\%$ , and  $\pm 0.3$  mg/L, respectively, while the DS18B20 sensor has an error of  $\pm 0.5^\circ\text{C}$ . The entire device was housed in an IP65-rated waterproof enclosure measuring  $380 \times 260 \times 120$  mm. The total hardware cost was 10,896,000 VND, as detailed in Table 1.

**Table 1.** Main components and hardware cost

| Component                  | Qty | Cost (VND)        |
|----------------------------|-----|-------------------|
| DFRobot Gravity pH sensor  | 1   | 1,674,000         |
| DFRobot Gravity EC sensor  | 1   | 1,944,000         |
| DFRobot Gravity DO sensor  | 1   | 4,644,000         |
| WeAct ESP32-C5 kit         | 2   | 658,000           |
| DS18B20 temperature sensor | 1   | 69,000            |
| OLED display 1.3 inch I2C  | 1   | 89,000            |
| IP65 waterproof enclosure  | 1   | 182,000           |
| Power, cables, other parts | -   | 1,636,000         |
| <b>Total</b>               |     | <b>10,896,000</b> |

An analysis of the cost structure shows that the three Gravity sensors accounted for approximately 76% of the total cost, with the optical DO sensor alone accounting for up to 43%. This represents a reasonable trade-off, as DO is the most critical parameter and requires high reliability. The remaining components, including the microcontrollers, display, protective enclosure, and accessories, are common components that can be easily replaced locally. Selecting the ESP32-C5 platform instead of expensive dedicated microcontrollers also enables the use of open-source software, shortens development time, and facilitates replication.



**Figure 2.** System hardware: (a) PCB with two ESP32-C5 and the OLED display; (b) assembly inside the waterproof enclosure

### 2.3. Temperature compensation and sensor calibration

Because pH, EC, and DO are all significantly affected by temperature, each measurement cycle begins by reading

the value from the DS18B20 sensor. This temperature value is then used to compensate the remaining sensors.

The output voltage of the pH sensor was converted according to the Nernst equation, in which the theoretical slope depends on the absolute temperature  $T$ , in K:

$$pH = 7.0 - (V - V_7) / (2.303 \cdot R \cdot T / F) \quad (1)$$

where,  $V$  is the measured voltage,  $V_7$  is the voltage at pH 7.0,  $R$  is the gas constant, and  $F$  is the Faraday constant.

Electrical conductivity was normalized to  $25^\circ\text{C}$  using a linear compensation coefficient:

$$EC_{25} = EC_T / [1 + \alpha(T - 25)] \quad (2)$$

where,  $\alpha = 0.02$ , equivalent to  $2.0\%/^\circ\text{C}$ , is the temperature coefficient characteristic of brackish water [6].

The dissolved oxygen concentration was corrected for temperature and salinity using the solubility table integrated into the DFRobot library, approximately following the relationship:

$$DO_{corrected} = DO_{measured} \cdot f(T, S) \quad (3)$$

where,  $f(T, S)$  is the correction coefficient that decreases with temperature and salinity  $S$ .

Sensor cleaning and calibration were performed every two weeks using pH 4.01 and 6.86 buffer solutions, and EC 1.413 mS/cm and 12.88 mS/cm standard solutions, to limit biofouling and sensor drift. The 5-minute sampling interval was selected to balance temporal resolution, sufficient to capture rapid fluctuations preceding nocturnal oxygen depletion events, with storage capacity, transmission bandwidth, and sensor lifetime.

### 2.4. Data transmission

Unlike common approaches that use intermediary platforms such as ThingSpeak or the MQTT protocol [22], the system sends data directly to a MySQL database on a private server. The communication node performs an HTTP POST request to a PHP endpoint, after which PHP parses the data packet and writes it to MySQL in real time. This approach eliminates dependence on third-party services and allows the research team to fully control data and storage.

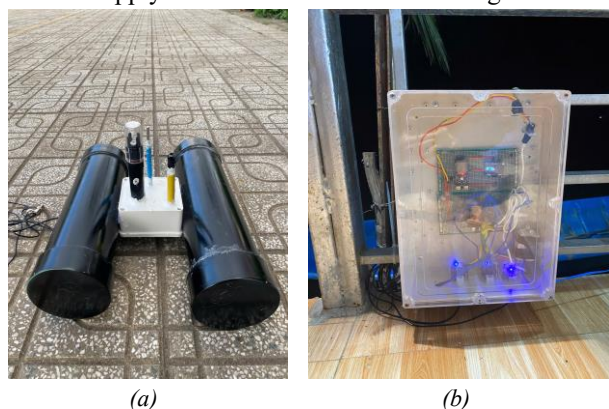
The web dashboard, developed using PHP [23], directly queries MySQL to display real-time and historical charts. When a parameter exceeds a safety threshold, for example when DO falls below 4 mg/L, the system automatically sends an email alert. The latency from sampling to display is less than 2 minutes. The firmware for the two microcontrollers was developed using Arduino IDE version 2.3.10, while the web dashboard used PHP version 8.4.12 and MySQL version 9.4.0.

### 2.5. Field deployment

The system underwent several versions before reaching the final deployment configuration, shown in Figure 3, with three main refinements. First, the design was changed from one ESP32 to two ESP32 microcontrollers, corresponding to the sensor node and the communication node, to separate signal acquisition from communication, thereby reducing timing conflicts and improving stability. Second, the probes were transferred to a floating PVC

platform consisting of two  $\Phi 114$  mm pipes and a central junction box, keeping the probes at a depth of approximately 30 cm and continuously submerged regardless of tidal fluctuations. Third, the electrical enclosure was moved from outdoors to indoors to avoid rain and rising water.

The system operated continuously from 1 February to 10 April 2026, for a total of 69 days, and was powered by a 5V/2A supply from the household electrical grid.



**Figure 3.** Field deployment: (a) float carrying the probes; (b) electronics enclosure

## 2.6. Data processing and quality control

The automated data quality control procedure on the server consisted of three steps.

First, a physical range check was performed to remove values outside plausible ranges, including pH values outside 6.0–9.5 and DO values outside 0–15 mg/L. Second, noise spikes were detected using a five-point moving median filter, with samples marked as outliers when they deviated from neighboring values by more than three times the median absolute deviation, MAD. Third, gaps caused by connection loss were retained without interpolation in order to preserve the integrity of the time series.

The cleaned data were stored in parallel as MySQL tables and CSV files for use in training predictive models in the next stage.

## 3. Results

### 3.1. Descriptive statistics

During the 69-day deployment, the system was expected to collect 19,870 samples at a 5-minute sampling interval and recorded 19,519 valid samples, corresponding to a data collection rate of 98.2%. The 351 missing samples, accounting for 1.8%, were mainly due to Wi-Fi disconnections, each lasting from 1 to 8 hours, two scheduled sensor cleaning and calibration events, and a few erroneous data packets. No hardware failure occurred throughout the monitoring period.

The descriptive statistics of the four main parameters are presented in Table 2, showing a wide range of variation characteristic of the coastal brackish-water environment of the Mekong Delta during the dry season.

In terms of the coefficient of variation, CV, calculated as the standard deviation divided by the mean, pH had the

lowest CV, at 2.1%, reflecting the high stability of the carbonate buffer system in brackish water. In contrast, DO had the highest CV, at 23.7%, because it was strongly governed by the photosynthesis–respiration cycle. Temperature, with a CV of 6.7%, and EC, with a CV of 9.6%, showed moderate variability. The DO distribution was clearly left-skewed, with a long tail toward low values, indicating that oxygen depletion events, although infrequent, had large amplitudes. This is an important feature that predictive models need to capture.

**Table 2.** Descriptive statistics of water quality parameters ( $n = 19,519$ ). Mean: average; SD: standard deviation

| Parameter                          | Mean  | SD   | Min   | Max   |
|------------------------------------|-------|------|-------|-------|
| Temperature ( $^{\circ}\text{C}$ ) | 29.21 | 1.96 | 22.70 | 36.60 |
| pH                                 | 7.92  | 0.17 | 7.30  | 8.60  |
| DO (mg/L)                          | 5.44  | 1.29 | 1.20  | 8.50  |
| EC (mS/cm)                         | 24.95 | 2.40 | 17.20 | 36.40 |
| Salinity (ppt)                     | 16.00 | 1.54 | 11.00 | 23.30 |

### 3.2. Communication performance and connection recovery

During the 69-day operation, the system recorded 24 separate data interruption events, with a median duration of 5 minutes, equivalent to one measurement sample, and a mean duration of 73 minutes. The longest event lasted 6 hours, on 21 March 2026, due to Wi-Fi disconnection, while two events of approximately 4 hours coincided with the scheduled cleaning and calibration procedures.

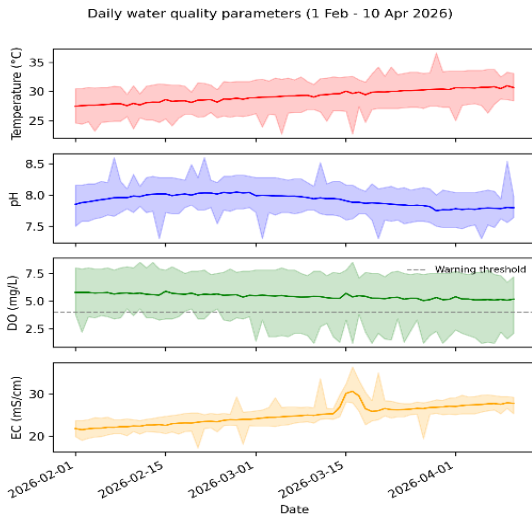
The latency from the sampling time to data visualization on the web dashboard remained below 2 minutes throughout the monitoring period. The system has not yet separately recorded the packet loss rate at the transmission level, distinguished from the complete disconnection events described above, nor the server response time. This is a limitation that should be addressed in the next version by adding a detailed transmission logging mechanism.

Regarding recovery from Internet connection loss, the current architecture does not include local buffer storage, such as an SD card, at the communication node. Therefore, samples collected during connection loss were skipped instead of being temporarily stored and resent after the connection was restored. This is an important improvement direction proposed for future studies to enhance data integrity under unstable network conditions in rural areas.

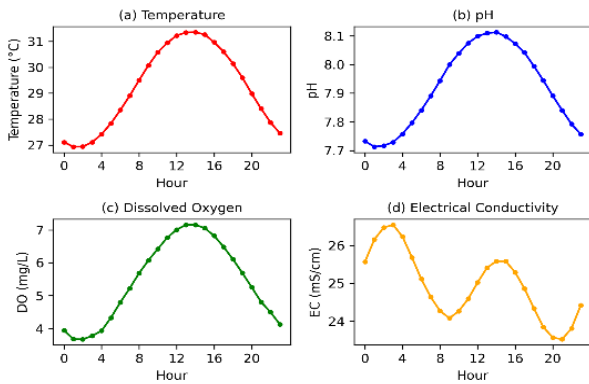
### 3.3. Temporal evolution and diurnal cycles

Figure 4 shows the daily evolution of water quality parameters in the pond. Temperature gradually increased from approximately  $28^{\circ}\text{C}$  in early February to more than  $31^{\circ}\text{C}$  in early April, consistent with the dry-season trend. EC also gradually increased due to intensified salinity intrusion as upstream discharge decreased.

Daily mean DO ranged from 5.0 to 5.9 mg/L, with a slight decreasing trend from approximately 5.7 mg/L during the first two weeks to about 5.2 mg/L during the final two weeks of the period, as increasing temperature reduced oxygen solubility. pH remained relatively stable around 7.8 – 8.0, with a mean of  $7.92 \pm 0.09$ , throughout the entire period.



**Figure 4.** Daily evolution of the four water quality parameters  
Average diurnal patterns of the four water quality parameters



**Figure 5.** Average diurnal patterns of the four water quality parameters

Analysis of the diurnal cycle, shown in Figure 5, indicates that temperature reached its maximum at 13:00–14:00 and its minimum at 01:00–02:00, with an average amplitude of approximately 4.4°C. DO closely followed this cycle: daytime photosynthesis increased DO concentration to its peak, whereas nighttime respiration reduced DO to its minimum at 01:00–02:00. This was the most dangerous period for shrimp, with an average fluctuation amplitude of approximately 3.5 mg/L.

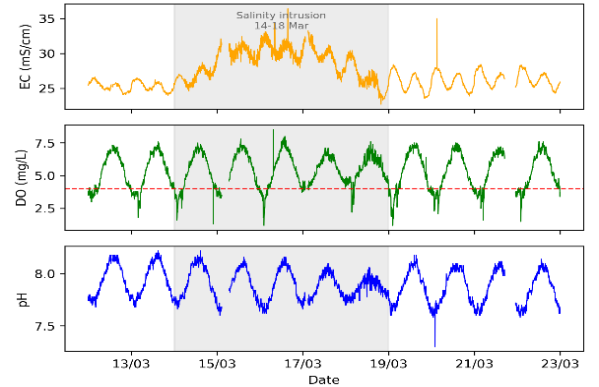
pH varied in phase with DO because photosynthesis consumed CO<sub>2</sub>, thereby increasing pH. EC exhibited two peaks per day, reflecting tidal influence. Understanding these cycles helps farmers proactively operate aeration systems during the night and early morning instead of reacting passively after shrimp have already experienced stress.

### 3.4. Oxygen depletion and salinity intrusion events

Among the 19,519 DO samples, 2,896 samples, accounting for 14.8%, were below the safety threshold of 4 mg/L. A total of 89.2% of oxygen depletion events occurred between 00:00 and 06:00, and almost no events occurred during the daytime. This confirms the biological nature of nocturnal oxygen depletion and highlights the value of providing early warning several hours in advance.

During the 69-day deployment, the system sent 87 email alerts, enabling farmers to activate aerators in a timely manner. The alert frequency gradually increased toward the end of the monitoring period, following the dry-season warming trend, which reduced oxygen solubility.

EC, DO and pH around the March 2026 salinity intrusion event



**Figure 6.** Salinity intrusion event during 14–18 March 2026

A distinct salinity intrusion event was recorded from 14 to 18 March 2026, as shown in Figure 6. EC increased rapidly from approximately 25 mS/cm to a maximum value of 36.40 mS/cm, equivalent to a salinity of approximately 23.3 ppt. This represented an increase of about 6 ppt within only 48 hours and coincided with a spring tide. The event was accompanied by strong DO fluctuations and several periods of low DO.

Farmers observed signs of reduced shrimp feeding during this period. This was a qualitative observation from field monitoring and was not quantified through production data, survival rate, or feed consumption. The system sent alerts within 5 minutes after the abrupt EC increase, allowing farmers to promptly conduct partial water exchange. However, due to the lack of quantitative data on yield and survival rate, the effectiveness of this mitigation measure in reducing losses cannot yet be confirmed with certainty and should be quantitatively evaluated in future deployments.

### 3.5. Validation against handheld measurement devices

To verify the accuracy of the IoT sensors under field conditions, eight reference measurements were conducted at evenly distributed times throughout the monitoring period using a calibrated handheld TDS/EC/pH/Temp meter and a Sera colorimetric dissolved-oxygen test kit, as shown in Figure 7. During each validation, the handheld measurement was taken immediately next to the IoT probe, at the same depth and time, to minimize differences caused by water stratification. The IoT value was averaged over a 5-minute window around the time of manual measurement to reduce the influence of instantaneous noise.

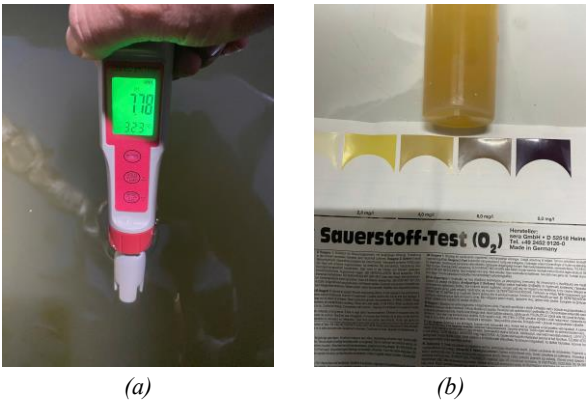
The summarized mean values from the eight validation measurements in Table 3 show that the mean absolute error, MAE, was 0.3°C for temperature, 0.07 pH units for pH, 0.2 mg/L for DO, and 0.5 mS/cm for EC. All errors were within the combined tolerances of the IoT sensors and reference devices, namely  $\pm 0.5^\circ\text{C}$ ,  $\pm 0.1$ ,  $\pm 0.3$  mg/L, and  $\pm 5\%$ , respectively, confirming that the

system provides measurements sufficiently accurate for shrimp pond management.

When expressed as percentages of the mean values, the corresponding relative errors were approximately 0.98% for temperature, 0.88% for pH, 3.25% for DO, and 2.02% for EC. These values were all low and suitable for threshold-based warning in pond management. The EC error tended to increase slightly during high-salinity periods, consistent with the nonlinear characteristics of conductivity sensors at high value ranges. Nevertheless, this error level did not affect the system’s ability to detect trends and issue alerts for abnormal events.

The frequency of eight validation measurements over 69 days, averaging approximately once every 8–9 days, was selected due to limitations in manpower and the cost of field travel with calibrated handheld devices to the pond. This frequency was lower than desired for firmly confirming accuracy throughout the entire 69-day operation. Because the validation measurements were summarized only as mean errors, as shown in Table 3, and were not recorded at each specific time point, this study cannot yet quantitatively evaluate the sensor drift trend between two consecutive calibration events, nor the separate effect of biofouling on measurement repeatability.

The current biweekly cleaning and calibration schedule was intended to limit these effects but has not yet been quantitatively evaluated before and after cleaning. Future studies should increase the validation frequency, for example to weekly measurements, and record errors at specific time points to systematically analyze sensor drift trends and the influence of biofouling.



**Figure 7.** Reference measurement devices:  
(a) handheld TDS/EC/pH/Temp meter;  
(b) Sera colorimetric dissolved-oxygen test kit

**Table 3.** Comparison between the system and a handheld meter over 8 reference measurements. MAE: mean absolute error

| Parameter   | Unit  | IoT (mean) | Handheld (mean) | MAE  |
|-------------|-------|------------|-----------------|------|
| Temperature | °C    | 30.4       | 30.6            | 0.3  |
| pH          | -     | 7.99       | 7.98            | 0.07 |
| DO          | mg/L  | 6.1        | 6.2             | 0.2  |
| EC          | mS/cm | 24.7       | 24.7            | 0.5  |

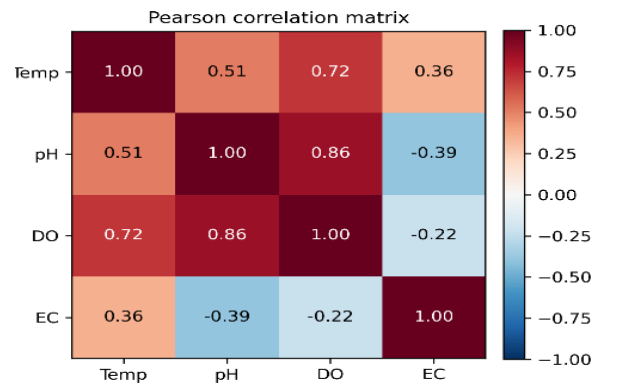
3.6. Correlation analysis among parameters

The Pearson correlation matrix, shown in Figure 8, clarifies the relationships among the continuously

monitored water quality parameters. Temperature and DO showed a strong positive correlation, with  $r = 0.72$ : daytime sunlight both warmed the water and promoted oxygen-generating photosynthesis, overriding the inverse relationship associated with solubility, which becomes more evident only at the seasonal scale.

pH and DO showed a very strong positive correlation, with  $r = 0.86$ , because photosynthesis both produces oxygen and consumes  $\text{CO}_2$ , thereby increasing pH. Temperature and pH showed a moderate positive correlation, with  $r = 0.51$ . In contrast, EC showed weak negative correlations with pH,  $r = -0.39$ , and DO,  $r = -0.22$ , indicating that high-salinity periods were accompanied by a slight reduction in biological productivity. The temperature–EC correlation was weak to moderate, with  $r = 0.36$ , confirming that salinity was mainly governed by tidal and hydrological factors, independently of the diurnal temperature cycle.

Given the large sample size,  $n = 19,519$ , all of the above correlation coefficients were highly statistically significant, with  $p < 0.001$ . These relationships correctly reflect the ecological dynamics of the pond, where photosynthesis–respiration processes link DO, pH, and temperature, while salinity is separately controlled by tides. This provides a quantitative basis for selecting input variables for multivariate predictive models: priority should be given to retaining parameters that provide complementary information, namely DO, temperature, and pH, while adding EC as an independent variable reflecting hydrological factors.



**Figure 8.** Pearson correlation matrix among the four continuously monitored parameters

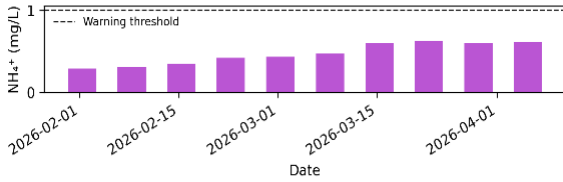
3.7. Ammonium,  $\text{NH}_4^+$ , Dynamics

Weekly manual measurements of  $\text{NH}_4^+$ , shown in Figure 9, remained below the warning threshold of 1.0 mg/L throughout the monitoring period, with a mean value of 0.47 mg/L. A temporary increase was recorded in the week immediately following the salinity intrusion event, peaking at 0.63 mg/L on 22 March. This may have been due to stress-induced increases in excretion and the accumulation of organic waste.

The low temporal resolution of this measurement, on a weekly basis, limited detailed analysis but confirmed that  $\text{NH}_4^+$  remained within the acceptable range for shrimp farming. Integrating an automatic  $\text{NH}_4^+$  sensor is

an important improvement direction for the next system version.

Weekly manual ammonium ( $\text{NH}_4^+$ ) measurements using the Sera test kit



**Figure 9.** Weekly manual ammonium ( $\text{NH}_4^+$ ) measurements using the Sera test kit

#### 4. Discussion

A data availability rate of 98.2% over 69 days of continuous deployment is a favorable result, comparable to or higher than those reported in related studies worldwide [14, 15, 16]. This reliability was achieved through several key factors: (i) a two-microcontroller architecture that separates sensor signal acquisition from Wi-Fi communication, thereby reducing timing conflicts; (ii) a floating PVC platform that maintains the probes at a stable depth regardless of tidal water-level fluctuations; (iii) the use of Wi-Fi and grid electricity, which is suitable for practical conditions in rural coastal areas of Vietnam; and (iv) a biweekly maintenance schedule to address biofouling.

Compared with many previous studies that were validated only in laboratories or tanks over short periods [12, 15], an important contribution of this study is the long-term field dataset, spanning 69 days, collected under actual commercial farming conditions and accompanied by quantitative validation against reference devices. The total hardware cost of 10.9 million VND for a single sensor set installed in one pond of approximately 20 ha in this study is many times lower than that of commercial monitoring stations, which range from 77 to 256 million VND [9, 11]. This indicates the potential for replication among small- to medium-scale farming households, from several hectares to several tens of hectares, with one monitoring point representative of the entire pond. For larger ponds or sites with complex topography that require multi-point monitoring due to spatial variability, additional sensor sets can be deployed, with the cost increasing linearly according to the number of monitoring points. The variation ranges and patterns of the monitored parameters are consistent with published data for brackish-water environments in the Mekong Delta [3, 4, 17], confirming that the collected dataset is ecologically representative and sufficiently reliable as input for machine learning models.

Table 4 compares the proposed system with several representative studies in terms of cost, number of parameters, sampling frequency, and field deployment duration. The proposed system stands out in terms of low cost, high sampling frequency, at 5 minutes, and long field deployment duration, at 69 days, with data validated against reference measurements. These are factors often lacking in studies that remain at the laboratory-scale testing stage. Compared with the study by Danh et al. [19], an IoT-based water quality monitoring system also deployed in the

Mekong Delta but for intensive shrimp ponds, the system in the present study was specifically designed for the integrated rice–black tiger shrimp rotational farming system and provided a longer field deployment duration together with quantitative validation against reference devices. Compared with two other domestic studies published in The University of Danang - Journal of Science and Technology, the system by Phat [20] focused on whiteleg shrimp, while the system by Thanh [21] targeted general water pollution monitoring; neither reported long-term field deployment data with quantitative accuracy validation as conducted in this study.

**Table 4.** Comparison of selected water quality monitoring studies

| Study            | No. of parameters   | Frequency | Deployment | Data transmission |
|------------------|---------------------|-----------|------------|-------------------|
| Chen et al. [12] | 4                   | 15 min    | Lab        | LoRa              |
| Lin et al. [13]  | 5                   | 1 min     | 30 days    | Wi-Fi             |
| Jais et al. [15] | 3                   | 10 min    | Tank       | Wi-Fi             |
| Proposed         | 4 + $\text{NH}_4^+$ | 5 min     | 69 days    | Wi-Fi (direct)    |

Note: “direct” means data are sent straight to a private MySQL server via HTTP POST, without an intermediary platform such as ThingSpeak (used by Lin et al. [13] and Jais et al. [15]).

The successful detection of the mid-March salinity intrusion event demonstrates the practical value of continuous monitoring. Manual measurements conducted only once or twice per day can easily miss the initial stage of a rapid EC increase, whereas the IoT system captured the event within 5 minutes and issued an immediate alert.

Several limitations should also be clearly noted. First, due to budget constraints, the current system has not yet integrated an automatic  $\text{NH}_4^+$  sensor; this important parameter is still measured manually on a weekly basis using a colorimetric test kit. Second, the system depends on household grid electricity; the next version will integrate solar batteries for deployment in ponds located far from residential areas. The present study has not directly measured the power consumption of the system. According to the manufacturer’s specifications, the ESP32-C5 microcontroller consumes a peak current of approximately 249–337 mA when transmitting via 2.4 GHz Wi-Fi and approximately 94–102 mA when receiving [24]. With two microcontrollers operating continuously, without using sleep mode, together with the current consumption of the three Gravity sensors and the OLED display, the system power consumption is preliminarily estimated to be in the range of 2–4 W at 5 V, equivalent to 50–100 Wh per day. This theoretical estimate needs to be directly measured, for example using a power meter, and optimized using deep-sleep mode between measurement cycles before calculating the appropriate battery capacity and solar panel size for standalone deployment.

Third, although the 69-day monitoring period was sufficient to demonstrate feasibility, it did not cover the entire annual integrated rice–black tiger shrimp farming cycle. Finally, sensor accuracy gradually decreases over time due to biofouling. This is a common issue in long-term water monitoring systems and should be addressed through active anti-biofouling designs.

## 5. Conclusion

This study designed, deployed, and field-evaluated a low-cost IoT system for real-time water quality monitoring in the integrated rice–black tiger shrimp farming system in the Mekong Delta over 69 consecutive days. The system cost approximately 10.9 million VND, achieved a data availability rate of 98.2%, and monitored four parameters, namely temperature, pH, DO, and EC, at 5-minute intervals.

Validation against a handheld meter confirmed that the measurement accuracy was within the sensor tolerances. The resulting dataset, comprising more than 19,500 quality-controlled observations, is available from the corresponding author upon request.

Future development directions include building multivariate time-series forecasting models, such as LSTM and ARIMA, to predict abnormal events 12 hours in advance, with the results to be presented in a separate publication; integrating solar batteries for standalone deployment; and expanding deployment across multiple ponds in other provinces of the Mekong Delta to establish a connected monitoring network.

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