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Multimodal Sensor Evaluation for Fish Pond Water Quality Monitoring

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ABSTRACT

Freshwater aquaculture requires continuous water quality monitoring because rapid changes in temperature, pH, dissolved oxygen, turbidity, total dissolved solids, and water level can affect fish health and pond productivity. This study evaluates a multimodal sensor system for real-time fish pond water quality monitoring and dashboard-based actuator control. The system integrates six sensors with Arduino Mega for signal acquisition, ESP32 for Wi-Fi communication, Firebase for cloud data storage and command exchange, and a Flutter dashboard for visualization and manual control. Field testing was conducted in two tilapia ponds with different initial conditions. Sensor performance was evaluated by comparing five measurable parameters with reference instruments using percentage error, accuracy, mean absolute error, and root mean square error, while turbidity was assessed through functional contrast testing and short-term stability because a turbidity reference instrument was unavailable. The average accuracy of the five validated parameters was 87.37% in pond 1 and 95.58% in pond 2. Temperature and water level showed the highest accuracy, above 98% in both ponds. Dissolved oxygen and total dissolved solids showed larger deviations, especially in pond 1, indicating sensitivity to field conditions and calibration stability. Actuator commands for the aerator and circulation pumps responded within 1-2 seconds under stable network conditions. The results show that the system is useful as a preliminary field-validated monitoring and semi-automatic control platform, but further work is required for long-term drift testing, turbidity validation using a commercial meter, and automatic control evaluation.

I. INTRODUCTION

Water quality is a determining factor in freshwater aquaculture because it affects fish metabolism, growth, stress response, behaviour, disease susceptibility, and survival. Parameters such as temperature, pH, dissolved oxygen (DO), turbidity, total dissolved solids (TDS), and water level may change continuously due to feeding, respiration, organic matter accumulation, aeration, rainfall, evaporation, and water exchange. When these changes are not detected promptly, pond managers may respond too late to prevent productivity losses or fish mortality[1][2][3][4].

Manual water quality monitoring is still widely used in small and medium-scale aquaculture. This approach generally depends on separate instruments and intermittent measurement schedules, so it is less suitable for detecting short-term changes in pond conditions. Internet of Things-based monitoring has been proposed as an alternative because sensors can be connected to microcontrollers and cloud platforms to provide real-time access to water quality data[5][6][7][8]. However, several previous systems monitored only limited parameters, were tested mainly in prototype conditions, or did not include a control function linked to the monitoring dashboard.

Previous studies have demonstrated the value of Internet of Things-based water quality monitoring in aquaculture. Some systems used pH, temperature, water level, or DO sensors, while others added notification or actuator features

[5]-[9]. Nevertheless, there is still a practical gap in field studies that simultaneously integrate six pond water quality parameters, evaluate sensor accuracy against reference instruments, describe the communication architecture and latency, and discuss sensor stability, scalability, and implementation cost. This gap is important because the practical use of such systems depends not only on successful data display but also on measurement reliability under real pond conditions.

Recent aquaculture monitoring studies have also explored dynamic water quality systems, cost-effective multi-parameter monitoring, portable Internet of Things devices, and low-cost Aquaculture 4.0 implementations[9]-[17]. These studies confirm that multi-parameter monitoring is technically feasible, but they also show that practical adoption depends on calibration reliability, field stability, communication performance, and implementation cost. Therefore, a field-oriented evaluation must report not only whether sensor data can be displayed, but also how accurate, stable, scalable, and operationally realistic the system is under real pond conditions.

Therefore, this study evaluates a multimodal sensor system for fish pond water quality monitoring and dashboard-based control. The main contributions of this study are: (1) integration of six water quality parameters in one cloud-connected system; (2) field implementation in two freshwater tilapia ponds with different initial conditions; (3) evaluation of five validated sensors using percentage error, accuracy, MAE, and RMSE; (4) additional short-term stability and correlation analysis to interpret field measurement behaviour; and (5) transparent discussion of control limitations, turbidity validation limitations, cost, scalability, and generalization.

TABLE I
COMPARISON WITH RELATED WATER QUALITY MONITORING STUDIES

Study	**Context**	**Parameters**	**Control feature**	**Testing context**	**Position of this study**
Wibisono and Jayadi [5]	Catfish pond	pH, temperature, water level	Yes	Field experiment	Limited sensor coverage compared with six-parameter evaluation
Yunior and Kusrini [6]	Aquaculture monitoring	pH, DO, temperature, turbidity	No	Monitoring system	Control function was not the main focus
Adriman et al. [8]	Prawn pond	pH, salinity, water level	Notification	Field monitoring	Different species and fewer quality parameters
Tyagi et al. [9]	Water monitoring	pH, water level	No	Prototype/system test	Limited aquaculture-specific validation
Abinaya et al.[18]	Aquaculture	Temperature, pH, turbidity and related parameters	Yes	Methodology/system design	Less emphasis on multi-pond sensor accuracy evaluation
This study	Tilapia ponds	Temperature, pH, DO, turbidity, TDS, water level	Manual dashboard control	Two real ponds	Sensor accuracy, MAE, RMSE, short-term stability, correlation, cost and scalability discussion

II. METHODS

A. Research Design and Site

This study used a quantitative experimental approach combined with system development. The research was conducted in tilapia culture ponds at the Centre for Quality Assurance Development of Vocational Education in Marine Affairs, Fisheries, Information and Communication Technology (BPPMPV KPTK), Gowa Regency, South Sulawesi, from October 2025 to February 2026. The field implementation was intended to evaluate system behaviour under actual aquaculture conditions rather than only in a laboratory prototype setting.

TABLE II
CONDITIONS OF THE EXPERIMENTAL PONDS

Parameter	**Pond 1**	**Pond 2**
Pond size	4 x 3 m	4 x 3 m
Pond height	1.09 m	1.09 m
Initial water level	75 cm	41 cm
Number of fish	200 fish	50 fish
Age of fish	about 1 month	more than 6 months
Initial water condition	Newly filled pond	About 2 months without water exchange
Main interpretation factor	Higher fish density but newer water	Lower water level, older water, older fish

B. System Architecture and Data Communication

The system architecture consisted of a sensor layer, an edge processing layer, a cloud layer, a user interface layer, and an actuator layer. The sensor layer collected six water quality parameters. The Arduino Mega performed signal acquisition and local preprocessing, while the ESP32 acted as the Wi-Fi gateway. Data were transmitted to Firebase and displayed through a Flutter dashboard. The same cloud channel was also used to store actuator commands generated from the dashboard.

Real-time monitoring in this study refers to periodic data acquisition and cloud synchronization within the configured reading interval of approximately 3-5 minutes. For control, the user selected an actuator command on the dashboard, the command state was written to Firebase, and the ESP32-Arduino relay circuit executed the ON or OFF command. Therefore, the implemented control was semi-automatic and dashboard-based. The automatic mode was designed conceptually but was not evaluated in this study.

TABLE III
DASHBOARD-BASED CONTROL STRATEGY AND EVALUATION STATUS

Parameter condition	**Threshold used in system**	**Dashboard action**	**Evaluation status**
Low dissolved oxygen	DO < 5 mg/L	Activate aerator	Manual ON/OFF response tested
High turbidity	Turbidity > 100 NTU	Activate circulation pump	Manual command mechanism available
Low water level	Water level < 54 cm	Activate water addition pump	Manual command mechanism available
Abnormal temperature	Temperature < 23°C or > 30°C	Activate circulation pump	Conceptual threshold; automatic control not tested
Abnormal pH	pH < 6.5 or > 8.5	Activate pH up or pH down pump	Conceptual threshold; automatic control not tested

The control logic was implemented as a human-in-the-loop mechanism. The dashboard displayed the parameter value and status, and the user selected the actuator command when corrective action was required. This design reduces overclaiming because the present study did not test closed-loop automatic recovery of water quality after actuator activation.

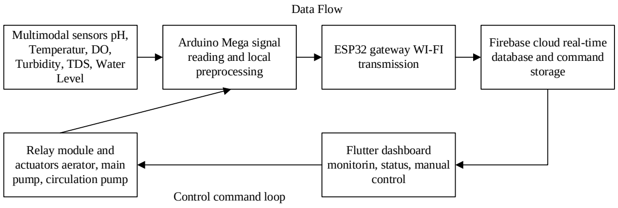


Figure 1. Revised technical architecture and data communication flow of the monitoring and control system.

C. Sensor Specification and Calibration

To provide a clear basis for sensor evaluation, this study documented the manufacturer specifications, calibration procedures, and reference instruments for each sensor. The pH sensor was calibrated using pH 4.0 and pH 7.0 buffer solutions. The temperature sensor was compared with a digital thermometer or multimeter reading. The DO sensor was prepared using the galvanic probe procedure and saturated oxygen calibration. The TDS sensor was compared with a reference TDS meter. The ultrasonic sensor was compared with direct water-level measurement using a measuring tape or marked pipe. The turbidity sensor was evaluated through functional contrast testing using clear water, pond water, and pond water mixed with soil, and through short-term reading stability because a commercial turbidity meter was not available during field testing.

TABLE IV
SENSOR SPECIFICATIONS AND CALIBRATION BASIS

Sensor	**Parameter**	**Measurement range**	**Manufacturer specification**	**Calibration/reference basis**
Gravity Analog pH Meter V2	pH	0-14 pH	±0.1 pH at 25°C	Two-point buffer calibration at pH 4.0 and pH 7.0
DS18B20	Temperature	-55 to 125°C	±0.5°C from -10 to 85°C	Compared with digital thermometer/multimeter
Gravity Analog DO Sensor	Dissolved oxygen	0-20 mg/L	Response up to 98% within 90 s; manufacturer accuracy not specified in product page	Saturated oxygen calibration and comparison with DO meter
DFRobot Turbidity Sensor	Turbidity	Analog output 0-4.5 V; operating temperature 5-90°C	Response time <500 ms; manufacturer accuracy not specified	Functional contrast test and stability analysis
Gravity Analog TDS Sensor	TDS	0-1000 ppm	±10% full scale at 25°C	Compared with TDS reference meter
Waterproof Ultrasonic Sensor	Water level	30-500 cm	±(1 + S x 0.5%); 3 mm resolution	Compared with direct meter measurement

D. Evaluation Metrics

Sensor accuracy was calculated only for parameters that had a reference instrument. The reference readings were treated as ground truth for field evaluation. For each measurement pair, percentage error and accuracy were calculated using (1) and (2). MAE and RMSE were then calculated using (3) and (4) to measure the absolute and squared deviations between sensor readings and reference values.

$$\text{(1)}\quad \text{Error\_i\%} = \left(\frac{X\_Sensor\_i - X\_reference\_i}{X\_reference\_i}\right) x\ 100\%$$

$$\text{(2)}\quad \text{Accuracy\_i}(\%) = 100 - Error\_i(\%)$$

$$\text{(3)}\quad MAE = \frac{1}{n}\Sigma(X\_reference\_i - X\_sensor\_i)$$

$$\text{(4)}\quad RMSE = \sqrt{\frac{1}{n}\Sigma(reference\_i - X\_sensor\_i)^2}$$

The average accuracy for each pond was calculated from the five parameters that could be validated against reference measurements: temperature, DO, pH, TDS, and water level. Turbidity was excluded from the average accuracy because no conventional turbidity reference instrument was available. To avoid overstating performance, turbidity was reported separately using functional response and short-term stability.

TABLE V
GROUND TRUTH AND EVALUATION METRICS

Parameter	**Reference basis**	**Evaluation metrics**	**Use in final accuracy**
Temperature	Digital thermometer or multimeter	Error, accuracy, MAE, RMSE	Validated quantitatively
Dissolved oxygen	Reference DO meter/multimeter	Error, accuracy, MAE, RMSE	Validated quantitatively
pH	Digital pH meter/multimeter	Error, accuracy, MAE, RMSE	Validated quantitatively
TDS	Reference TDS meter/multimeter	Error, accuracy, MAE, RMSE	Validated quantitatively
Water level	Measuring tape or marked pipe	Error, accuracy, MAE, RMSE	Validated quantitatively
Turbidity	No commercial turbidity meter available	Functional contrast test, range, SD, CV	Not included in average accuracy

E. Stability and Correlation Analysis

Short-term stability and correlation analysis were added to strengthen the interpretation of field measurements. Stability was evaluated using the coefficient of variation (CV), calculated as the ratio of standard deviation to the mean of each parameter. Obvious technical anomalies, such as zero values in temperature, water level, or dissolved oxygen readings, were excluded from stability and correlation calculations. Correlation analysis was used only as an exploratory interpretation of co-movement between monitored parameters, not as causal evidence.

F. Procedure and Anomaly Treatment

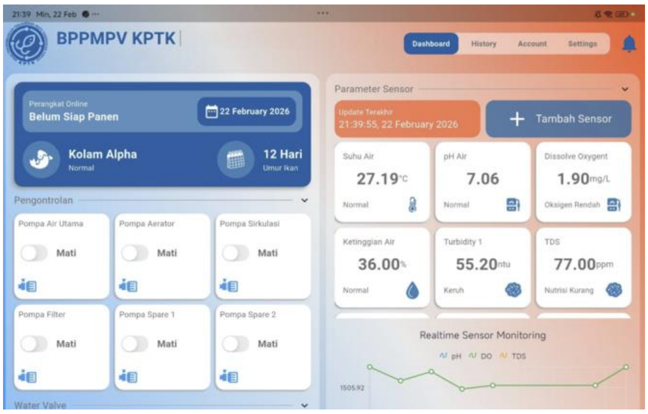
The field-testing procedure followed five sequential stages. First, sensor calibration was performed using appropriate calibration media and reference instruments. Second, the IoT system collected sensor readings periodically and stored them in Firebase. Third, manual validation was conducted by comparing sensor readings with reference measurements for temperature, DO, pH, TDS, and water level. Fourth, performance was analysed using percentage error, accuracy, MAE, and RMSE. Fifth, actuator response was tested by sending ON and OFF commands from the dashboard and observing relay response.

Technical anomalies were treated conservatively. Zero readings or values that were clearly inconsistent with adjacent measurements were identified as temporary technical anomalies, not as actual water quality changes. Possible causes include cable disturbance, unstable power supply, humidity around the device, sensor position changes, and analog reading noise. These anomalies were excluded from stability and correlation calculations but were still reported as implementation limitations.

III. RESULTS

A. Real-Time Monitoring and Control Response

The developed system successfully displayed six pond water quality parameters on the dashboard. The dashboard presented numerical readings, status categories, and manual actuator controls. During field testing, the control feature operated the aeration pump, main pump, and circulation pump through relay commands. The observed response time for ON and OFF commands was 1-2 seconds when the network connection was stable. This value represents dashboard-to-actuator command response, not the complete sensor data sampling cycle.



Perangkat Online: Belum Siap Panen

22 February 2026

Kolam Alpha: Normal

12 Hari: Umur Ikan

Update Terakhir: 21:39:55, 22 February 2026

Suhu Air: 27.19°C, Normal

pH Air: 7.06, Normal

Dissolve Oxygent: 1.90mg/L, Oksigen Rendah

Ketinggian Air: 36.00%, Normal

Turbidity 1: 55.20ntu, Keruh

TDS: 77.00ppm, Nutrisi Kurang

Pompa Air Utama: Mati

Pompa Aerator: Mati

Pompa Sirkulasi: Mati

Pompa Filter: Mati

Pompa Spare 1: Mati

Pompa Spare 2: Mati

Figure 2. Monitoring dashboard used for water quality visualization and manual actuator control.

Figure 3. Field implementation of the device in freshwater aquaculture ponds.

TABLE VI
ACTUATOR CONTROL RESPONSE

Actuator	Command	Response time	Result
Aeration pump	ON	1-2 s	Successful
Main pump	ON	1-2 s	Successful
Circulation pump	ON	1-2 s	Successful
Aeration pump	OFF	1-2 s	Successful
Main pump	OFF	1-2 s	Successful
Circulation pump	OFF	1-2 s	Successful

B. *Water Quality Monitoring Results*

The two ponds showed different water quality patterns. Pond 1 had a higher initial water level and newly filled water, while pond 2 had lower water volume and older water. These differences affected the observed sensor values and helped explain the different accuracy levels between ponds. Pond 2 had low dissolved oxygen throughout testing, indicating a real pond condition requiring corrective management rather than only sensor error.

TABLE VII
SUMMARY OF MONITORING RESULTS IN TWO PONDS

Parameter	Pond 1	Pond 2	Interpretation
Temperature	27.06-28.44°C	26.44-27.38°C	Both ponds were within the normal temperature range.
Dissolved oxygen	4.42-5.72 mg/L	1.34-1.63 mg/L	Pond 2 was consistently below the recommended level.
pH	Mostly normal	Several readings below normal	Pond 2 showed more acidic tendencies.
TDS	Low	Low, with several spikes	Both ponds were classified as low by the system.
Water level	Decreased during testing	Low and relatively stable	Pond 1 showed real decrease due to wall leakage; pond 2 started low.
Turbidity	Stable, mostly 25.56-55.16 NTU after excluding one zero anomaly	Stable, 53.56-71.93 NTU	Useful for observing changes, but not validated against a turbidity meter.

C. *Accuracy, Error, MAE, and RMSE*

The validated parameters showed different performance levels. Temperature and water level sensors performed consistently well in both ponds, with accuracy values above 98%. The DO sensor showed lower accuracy, especially in pond 1, with an average accuracy of 79.50%. The TDS sensor showed the largest contrast between ponds, with 70.66% accuracy in pond 1 and 98.41% in pond 2. This result indicates that TDS measurement was more sensitive to field conditions, sensor placement, and calibration stability.

TABLE VIII
ACCURACY, ERROR, MAE, AND RMSE OF VALIDATED SENSORS

Parameter	Pond 1		Pond 2		MAE	RMSE
	accuracy (%)	error (%)	accuracy (%)	error (%)		
Temperature	98.56	1.44	99.03	0.97	0.33 °C	0.37 °C
Dissolved oxygen	79.50	20.50	85.02	14.98	0.63 mg/L	0.70 mg/L
pH	89.91	10.09	96.96	3.04	0.45 pH	0.55 pH
Total dissolved solids	70.66	29.34	98.41	1.59	4.74 ppm	9.36 ppm
Water level	98.20	1.80	98.47	1.53	0.87 cm	1.28 cm
Average of validated parameters	87.37	12.63	95.58	4.42	-	-

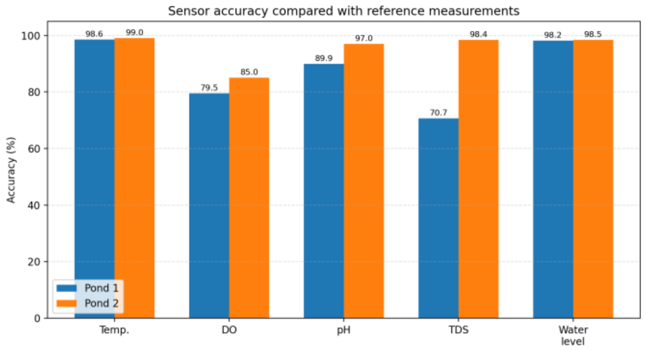


Figure 4. Comparison of sensor accuracy in pond 1 and pond 2.

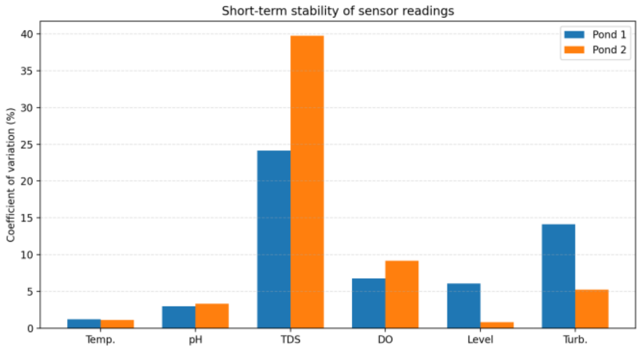


Figure 5. Coefficient of variation for short-term sensor stability.

D. *Short-Term Stability and Turbidity Evaluation*

The stability analysis shows that temperature and water level had the smallest relative variability, while TDS had the highest variability. In pond 1, TDS had a CV of 24.13%, and in pond 2 it reached 39.76%. This supports the finding that TDS was less stable than temperature and water level. Turbidity showed a CV of 14.13% in pond 1 and 5.22% in pond 2 after excluding a zero anomaly. Although this cannot replace validation against a commercial turbidity meter, it provides a clearer basis for interpreting turbidity as a short-term monitoring indicator.

TABLE IX
SHORT-TERM STABILITY OF SENSOR READINGS

Parameter	**Pond 1 CV (%)**	**Pond 2 CV (%)**	**Interpretation**
Temperature	1.22	1.12	Lower CV indicates more stable short-term readings
pH	2.97	3.33	Lower CV indicates more stable short-term readings
TDS	24.13	39.76	Lower CV indicates more stable short-term readings
DO	6.78	9.14	Lower CV indicates more stable short-term readings
Water level	6.08	0.81	Lower CV indicates more stable short-term readings
Turbidity	14.13	5.22	Lower CV indicates more stable short-term readings

E. *Exploratory Correlation Between Water Parameters*

Exploratory correlation analysis was added to enrich the interpretation of field measurements. In pond 1, DO showed a positive correlation with temperature (r = 0.82) and water level (r = 0.73), while it had a negative correlation with turbidity (r = -0.64) and TDS (r = -0.46). These patterns are consistent with the field observation that decreasing water level and increasing particulate conditions may coincide with lower oxygen conditions. In pond 2, correlations were weaker for most parameters because DO remained consistently low and the pond started with a lower water volume. The strongest relationship in pond 2 was between temperature and pH (r = 0.79). These results should be interpreted as co-movement patterns during short-term monitoring, not as causal relationships.

TABLE X
SELECTED CORRELATIONS BETWEEN WATER QUALITY PARAMETERS

Parameter pair	**Pond 1 r**	**Pond 2 r**	**Interpretation**
Temperature - DO	0.82	0.24	Strong positive relationship only in pond 1
Water level - DO	0.73	0.31	Higher water level coincided with higher DO, especially in pond 1
Turbidity - DO	-0.64	-0.26	Higher turbidity tended to coincide with lower DO
TDS - DO	-0.46	-0.07	Moderate negative relationship in pond 1
TDS - turbidity	0.73	0.36	Dissolved solids and turbidity tended to increase together
Temperature - pH	-0.02	0.79	Different co-movement pattern between ponds

IV. DISCUSSION

The results confirm that the proposed system can integrate six water quality parameters into a single monitoring platform and operate manual actuator control through a dashboard. Compared with manual measurement using separate instruments, the integrated dashboard reduces monitoring fragmentation and supports faster situational awareness for pond managers. The contribution of this study is therefore not merely the use of sensors and microcontrollers, but the field evaluation of a multimodal monitoring system under two different pond conditions with explicit accuracy, error, MAE, RMSE, stability, and correlation analysis.

The difference between pond 1 and pond 2 is an important finding rather than only a measurement inconsistency. Pond 1 had newly filled water and a higher initial water level, but several TDS readings deviated from the reference and reduced the average accuracy. Pond 2 had older water and lower water volume, which explains the consistently low DO values, but the validated sensors except DO show high agreement with reference measurements. This indicates that the two ponds represented different field challenges: pond 1 highlighted sensor deviation and water level loss, whereas pond 2 highlighted poor aquaculture water condition.

The low DO condition in pond 2 should also be interpreted as an environmental finding. During testing, dissolved oxygen remained below the expected level even after the aerator had been activated earlier. This suggests that low DO was not only a sensor problem, but also reflected pond conditions such as low water volume, older water, organic accumulation, and possible plankton density. Low dissolved oxygen is a critical stressor in fish physiology and can affect fish from organism-level behaviour to molecular response[16]. In contrast, the declining water level observed in pond 1 was consistent with field identification of leakage in the pond wall. These examples show that the system can support problem identification, but the corrective effect of actuator operation still requires separate before-after testing.

The best sensor performance was obtained from temperature and water level measurements. The DS18B20 produced small deviations, while the ultrasonic water level sensor was consistent with manual measurements. These parameters are physically more stable and less affected by chemical reactions, probe fouling, or electrode drift. In contrast, DO and TDS measurements are more sensitive to calibration, water mixing, probe position, suspended particles, organic load, and electrical noise. Previous studies also emphasize that calibration reliability and adaptive IoT measurement procedures are central to the accuracy of aquatic sensor systems[18][21]. This explains why their performance was more variable in field conditions.

The control feature must be interpreted carefully. The system successfully activated and deactivated actuators within 1-2 seconds under stable network conditions, but this study did not quantitatively test the extent to which actuator activation restored DO, turbidity, or water level to a target range. Therefore, the revised manuscript avoids claiming fully automatic control or proven water quality recovery. The current system should be described as a real-time monitoring system with dashboard-based semi-automatic control.

The turbidity sensor remains a methodological limitation. It was able to distinguish clear water, pond water, and extremely turbid water during functional testing, and its field readings were stable over the observation period. However, because no commercial turbidity meter was available, quantitative turbidity accuracy could not be calculated. For this reason, turbidity was excluded from the average accuracy calculation and should be validated in future work using a standard turbidity meter.

From the perspective of implementation cost and scalability, the prototype required an estimated hardware cost of approximately IDR 10.428 million. The dissolved oxygen sensor was the most expensive single component at about IDR 3.7 million, while the temperature, pH, TDS, turbidity, water level, microcontroller, relay, power, enclosure, and wiring components formed the remaining cost structure. This cost profile indicates that the complete six-parameter prototype may be more suitable for training centres, institutional ponds, or farmers that require detailed monitoring. For small farmers, modular deployment may be more realistic: temperature, pH, TDS, and water level sensors can be installed first, while DO and turbidity sensors can be added when the budget and monitoring needs increase. Scaling the system to more ponds also requires attention to waterproofing, stable power supply, sensor maintenance, network coverage, cloud database structure, and periodic recalibration.

The generalization of the results is limited to freshwater tilapia ponds with conditions similar to the test site. Application to other fish species, pond types, stocking densities, or water sources requires recalibration of threshold values and additional validation because optimal DO, pH, temperature, turbidity, TDS, and water level may differ across aquaculture systems. Therefore, the proposed system should be viewed as a field-validated prototype for similar freshwater pond environments, not as a universal monitoring solution for all aquaculture contexts.

V. LIMITATIONS

This study has several limitations. The observation period was short and did not represent seasonal variation. The turbidity sensor could not be validated quantitatively because a commercial turbidity meter was unavailable. The control feature was evaluated only in manual dashboard mode, so the effectiveness of automatic threshold-based control was not measured. The current evaluation also did not include long-term sensor drift, battery or power resilience, or multi-location deployment. These limitations are important for interpreting the system as a preliminary field-validated platform rather than a fully mature industrial solution.

VI. CONCLUSION

This study evaluated a multimodal sensor system for fish pond water quality monitoring and dashboard-based control. The system integrated six parameters and was implemented in two freshwater tilapia ponds. Five parameters were validated quantitatively against reference measurements, while turbidity was evaluated separately through functional response and short-term stability. The average accuracy of the validated sensors was 87.37% in pond 1 and 95.58% in pond 2. Temperature and water level sensors showed the strongest performance, whereas DO and TDS required further calibration and field stabilization. Actuator commands responded within 1-2 seconds under stable network conditions, but the control function remained manual and did not yet evaluate automatic water quality recovery. The system is therefore best described as a preliminary field-validated monitoring and semi-automatic control platform. Future research should validate turbidity with a commercial meter, conduct longer-term sensor drift testing, implement automatic threshold-based control and warning notifications, and evaluate the system across more ponds, species, and water management conditions.

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