17(3) 627-638, Autumn 2025

Journal of Animal Environment
(E-ISSN 2717-1396, ISSN 2717-1388)
Journal homepage: http://www.aejournal.ir

Original Research Paper

Sensor-Based Water Quality and Habitat Monitoring for Sustainable Aquatic Animal Environments

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Key Words

Habitat assessment, Plankton community structure, Gradient Boosted Decision Trees (GBDT), Sustainable aquaculture management, Environmental performance.

Abstract

The intricate management of aquatic animal production systems must be sustainable to ensure permanent and precise evaluation of water quality and habitat environmental conditions that determine the health and welfare of animals in addition to the overall performances of the environment. The present paper examined whether a sensor-based monitoring system can be beneficial in monitoring essential physicochemical and ecological parameters in freshwater aquaculture ponds. Dissolved oxygen, temperature, pH, turbidity, chlorophyll-a, and ammonia and nitrate concentration were also measured at various pond depths under seasonal production cycles and also compared with fish health parameters, growth performance, and survival rates. Factors associated with habitat, such as the stability of water depth, dynamics of plankton communities, and the quality of sediments were also studied at the same time to measure more extensive ecosystem operations. The outcomes showed moderate correlations between short term change of dissolved oxygen and ammonia on disturbed feeding behaviour, elevated physiological stress, and high mortality. The accumulation of nutrients seasonally caused the high turbidity and changes in plankton constructions, which also caused changes in growth pattern and feed usage. Sensors based monitoring management interventions (e.g. optimised aeration scheduling, water exchange, and feed adjustment improvement) led to significant improvements in water quality maintenance, fish growth rates, and less nutrient-enriching effluent released. Generally, the paper has shown that less sophisticated, non-network sensor monitoring systems can play a significant role in enhancing water quality management, ensuring the welfare of aquatic animals and facilitating the role of environmentally friendly pond-based aquaculture.

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Received: 19 June 2025; Revised: 30 July 2025; Accepted: 29 August 2025; Published: 30 October 2025
(DOI): 10.70102/AEJ.2025.17.3.51

Introduction

Aquaculture has emerged as a key ingredient to the world food production, and environmental sustainability of aquacultures is now a central issue to the health of animals, environmental performance, and sustainability. The water quality in pond-based systems is very volatile and the dynamics of major physicochemical parameters in the water, which include dissolved oxygen (DO), temperature, pH, turbidity, ammonia, and nitrate, and chlorophyll-a, directly affect fish welfare, growth, and survival. Past research highlights that immediate analysis of such parameters contributes significantly to its early identification of stress and risk of mortality especially in intensive production environments where, the variability of the environment is high (Ajith et al., 2020; Billah et al., 2019). With the increase in aquaculture, it will be more challenging to maintain a constant state of water quality, and thus the need to ensure continuous monitoring plans to ensure the biological and biological data of the changing environment is accurately recorded.

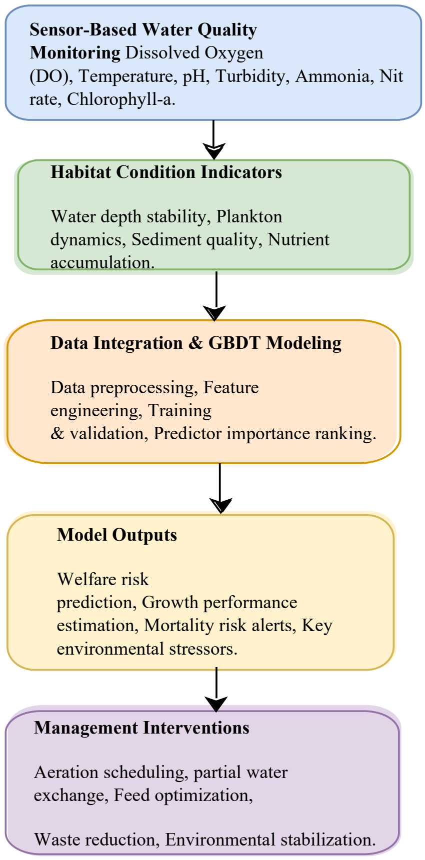

Figure 1: Conceptual Framework of Sensor-Based Aquaculture Water Quality and Habitat Monitoring System

Manual sampling techniques, though commonly used, have been found to have a number of limitations such as the intensity of labour, low time resolution and slow reaction to important events. Such limitations diminish the capacity of the farmers to apply timely management interventions particularly at night when there is a DO depletion or spike of ammonia. To become more reliable and provide much better precision, recent advances in sensor technology and systems that can be supported by the IoT have become an option to gather high-frequency, multi-depth water quality data (Kiruthika et al., 2017; Manoj et al., 2022; Shete et al., 2024). These systems have the capability of giving a more holistic picture of the pond environment by marrying measurements of habitat attributes that include water depth stability, planktons, and sediment quality- each of which is an important ecological component in nutrient cycling, productivity, and fish performance. The conceptual diagram of sensor-based monitoring applied in this study is represented in (figure 1).

All this means that in conjunction with environmental monitoring, an increased interest in analytical tools able to interpret complex multivariate data produced by sensor networks is being realised. Trees based machine learning algorithms have been popular due to their capability to employ nonlinear interactions in between water quality variables and their capacity to predict biological outcomes with high accuracy. GBDT (e.g., XGBoost and LightGBM) is particularly well-adapted to aquaculture systems, as they have strong predictive power, they can effectively predict with noisy sensor data, and the importance ranking of key stressors is interpretable (Islam et al., 2024; Manoj et al., 2022; Wu et al., 2023). Through these capabilities, GBDT will be able to contribute to real-time decision-making so that farmers can start to predict the risk posed to the environment by environmental factors anaerobically before they have a detrimental impact on fish health or production levels (Egash & Teyene, 2023).

In tandem with these developments, the current study examines the use of sensor-based monitoring system in measuring the water quality and environment, as well as in determining the water quality and conditions of freshwater ponds in aquaculture production throughout production seasons. The study objectives include in the following: (i) determining the capacity of sensor measurements to detect the hysteria environmental fluctuations, (ii) testing the links between the indicators of water quality/ habitat and fish health and growth performance, (iii) using a GBDT model to define the most powerful predictors of welfare impairment and mortality risk, and (iv) determining the importance of monitoring-based management intervention like aeration timing, partial water exchange, and optimal feed. Such comprehensive environmental and data-based methodology allows the study to be helpful in the creation of feasible and cost-efficient measures to control sustainable pond-based aquaculture.

Literature Review

One of the most important issues in the aquaculture system that determines fish health and welfare is the quality of water. Direct physiological effects of various physicochemical stressors like dissolved oxygen (DO), temperature, pH, turbidity, ammonia, nitrate and the abundance of chlorophyll-a on growth, metabolism and survival are observed. Sudden DO swings are capable of causing quick stresses, inhibiting the feeding habit and increasing the vulnerability of mortality particularly in ponds with high populations (Ajith et al., 2020; Billah et al., 2019). On the same note, ammonia concentration worsens irritation of the gills, impairs osmoregulation, and increases vulnerability to ill health, which adds to the destruction of production at high levels (Manoj et al., 2022). Advanced turbidity and nutrient cycles also contribute to the light penetration, phytoplankton growth and dissolved oxygen patterns, and therefore the ecological stability of pond environment. The factors listed in Table 1 are summarised results of associated studies and demonstrate the significance of these major parameters in aquaculture surveillance.

The development of sensor technologies has revolutionised the monitoring of aquatic environmental conditions because it is now possible to continuously monitor the water quality using multiple parameters. Microcontroller-based systems are now available at low prices, and they can simultaneously monitor DO, temperature, pH, turbidity and nutrient with better precision and time resolution than possible with manual sampling (Kiruthika et al., 2017; Medina et al., 2022; Shete et al., 2024). This is in contrast to traditional approaches that commonly do not provide timely information on the environment since they fail to identify the immediate changes taking place, sensor-based surveillance provides real-time data that is required to detect the occurrence of critical events like DO crashes or ammonia spikes. The research has identified a few studies to state that automation of sensing platform deployment in aquaculture systems increases the decision-making capacity, operational delays, and, eventually, more resilient managerial practises (Loh et al., 2023; Palconit et al., 2021; Srivastava et al., 2021). Such technologies have also been used more recently as the issues of aquaculture intensification across the globe require the need to stabilise the environment and production.

In addition to physicochemical surveillance, ecological balances that should be maintained in the aquaculture ponds must be arrived at through knowledge of the habitat features. The dynamics of plankton is a core element of nutrient cycle and natural food supply which determines the productivity of the pond and water quality. Changes in the plankton structure may reflect nutrient imbalances or pattern of entropy, which directly influences the oxygen concentration and development of fish (Islam et al., 2024). Another factor that leads to internal nutrient loading is the quality of the sediment, such as organic matter accumulation and nutrient accumulation further leads to internal nutrient loading, especially in warm seasons. Ecologically significant is stable water depth, and this aspect varies depending on the changes in depth affecting thermal stratification, distribution of dissolved oxygen, and habitat suitability. These habitat indicators can be used to give a more global ecological view which can enhance physicochemical monitoring which is sensor-based and is more holistic in terms of pond ecosystem functionality.

Machine learning (ML) methods have become popular in aquaculture over the last few years to analyse complex environmental data and make predictions of biological responses (Sarumathiy et al., 2024). The tree-based ensemble models, especially the Gradient

Boosted Decision Trees (GBDT) has demonstrated excellent results in modelling nonlinear relationships between the variables of water quality and fish health results (Manoj et al., 2022; Wu et al., 2023). LightGBM and XGBoost are BDT techniques that are highly suitable in sensor-generated tabular datasets because they are tolerant to noise, model the complex relationship between variables, and produce understandable feature importance scores. Other previous works which utilise ML methods to forecast DO variations, mortality, and algal blooms, as well as growth patterns of aquaculture systems have proved the validity of data-driven frameworks to proactive management (Ajith et al., 2020; Shete et al., 2024; Wu et al., 2023). ML in conjunction with real-time observation is an effective strategy to increase the sustainability of the environment and efficiency of operations in contemporary aquaculture.

Table 1: Summary of Existing IoT- and Sensor-Based Water Quality Monitoring Studies

Study	Technology / System Used	Parameters Monitored	Key Findings
Ajith et al., 2020	IoT-based smart water quality monitoring with cloud integration	DO, pH, temperature, turbidity	Enabled real-time data access and automated alerts for water quality deviations
Billah et al., 2019	Real-time fish farm monitoring using embedded sensors	DO, temperature, pH	Improved accuracy of water quality measurements and early stress detection
Manoj et al., 2022	IoT + underwater sensors for aquaculture monitoring	DO, pH, temperature, conductivity	Highlighted benefits of multi-sensor networks for continuous monitoring
Medina et al., 2022	Low-cost open-source buoy system for remote monitoring	DO, temperature, pH, conductivity	Demonstrated affordability and feasibility for decentralized aquaculture farms
Shete et al., 2024	IoT-enabled real-time monitoring for aquaculture ponds	DO, pH, ammonia, temperature	Achieved effective real-time assessment and improved management interventions

Methodology

Experiment was tested in pond aquaculture freshwater production under semi intensive management. All ponds were of similar sizes at about ___ m 2 (insert actual size), with strata of depth to represent the diversity of variation of water quality with depth; the surface (020 cm), the mid-water (2060 cm), and the bottom (>60 cm). Stocking density was according to the standard regional practises of fish/m 3, fish were fed at 2-4% body weight as per their development stage. The feeding was done two times a day, and climatic conditions were defined by warm seasonal changes towards subtropical regions. These parameters of the environment and transactions offered a realistic framework of assessing sensor-based surveillance of physicochemical and habitat parameters across a seasonal production cycle.

A sensor array of many parameters was installed to ensure that the measurements of dissolved oxygen (DO), water temperature, pH, turbidity, ammonia, nitrate, and chlorophyll-a were done continuously. The vertical fluctuations were captured throughout the day by installing sensors in every desired layer at depth of the water at a floating mounting system and submerged mounting system. Logging was made at the time rate of 1 at the order of 20 minutes and then data was downloaded after every week was passed to analyse them. Seasonal check-ups were made to trace changes at the pre-monsoon, monsoon, and post-monsoon times so that the environmental changes which normally occur in nutrient cycles, organic matter build-up, and algal growth could be evaluated. This provided high-resolution and longitudinal level of environmental data to be used in the connection of water quality changes with changes in the biological responses.

Measurements of sensor were conducted simultaneously with the habitat condition assessment. To monitor any changes caused by evaporation, rain and water exchange practises, calibrated depth gauges were used to record the water depth stability. Sampling of the planktons was done on weekly basis using horizontal and vertical net tows and then placing under a microscope using microscopies to identify and measure the population and quantities of the plankton to assess the trends in composition and productivity of the community. To determine the organic matter content, nutrient load, and the accumulations of the sludge, the sediment samples were gathered on a seasonal basis at the bottom of the pond. These habitat indicators were used in addition to the physicochemical measurements as it gave a picture of the ecosystem level of nutrient cycling, primary productivity and the overall environmental balance.

The health and Growth performance of fish was tracked in terms of behavioural and physiological parameters. The feeding behaviour was observed on a daily basis to determine the deviation as a result of stress or low water quality. Stress response marking took into account erratic swimming, gasping on the surface, gill discolouration and presence of mucus. The performance by growth was measured after every two weeks and through the use of usual indices, namely Specific Growth Rate (SGR), Feed Conversion Ratio (FCR), and percentage of survival. Mortalitys were noted when accompanied by the corresponding measurements of the water quality to learn the associations between environmental variations, namely the DO dips and ammonia spikes, and the biological outcome. The metrics were dependent variables that were further modelled.

All sensor datasets were pre-processed before being subjected to machine learning analysis to better the performance of the models and the quality of data. These involved deletion of either missing or erroneous readings, smoothing of noise by time, and normalisation of variables where necessary. Derived indices were made to more effectively indicate dynamic environmental processes such as a DO fluctuation index of short-term variability, an ammonia accumulation rate of nutrient build up, and turbidity-nutrient interaction to measure eutrophication potential. There were also seasonal categorical variables that were produced in order to include climatic factors in the model. Gradient Boosted Decision Trees (GBDT) were used to examine the complicated association among environmental predictors and biological outcomes through LightGBM and XGBoost. All physicochemical and habitat indicators were used as input features and the welfare risk classification and growth rate regression were the target outputs. The data were divided into the training and testing set in 70:30 proportion and the hyper parameters were optimised through cross-validation. Accuracy, F1-score and ROC-AUC were used to evaluate Model performance on classification tasks, and RMSE and R2 were used to evaluate Model performance on regression. The most important environmental drivers that influenced fish welfare and performance were determined using feature importance and SHAP based interpretation.

Results and Discussion

It was found that spatiotemporal analysis of water quality parameters showed that there is significant variation between pond depth layers as well as over seasonal cycles. There were strong oscillations of Dissolved oxygen (DO), and the night-time decreases were sharp and noticeable especially in warmer seasons. These lows were most pronounced in the bottom layers where organic decomposition was higher thus consuming more oxygen. Within concentrations of ammonia, depth-related distributions were also clearly observed with the greatest concentrations following feeding incidents and times of low water exchange. Turbidity was upgrading seasonally, and also with the build-up of nutrients and phytoplankton development. Table 2 presents the summary of descriptive statistics of critical parameters by sampling intervals. Altogether these trends indicate dynamic nature of the pond environment and the need to monitor it with high-resolution in order to capture short-lasting, although biologically relevant lapses of stress.

The habitat-level measurements also indicated the effect of ecosystem dynamics on the quality of water and the entire pond operation. Light was again altered by seasonal accumulation of nutrients leading to an increase of chlorophyll-a values and increased turbidity, changing primary productivity. The analysis of plankton community showed the tendencies to achieve the dominance of opportunistic algae species at the time of nutrient enrichment to decrease the diversity and alter food web relations. These changes affected the supply of the natural food sources of fish and increased the heterogeneity of the spatial structure of the water column. Sediment analysis showed that organic matter and nitrogenous compounds piled up over time and were especially present during the post-monsoon months which enhanced internal recycling of nutrients and enabled the maintenance of high turbidity levels. The existence of such trends in habitat highlights the fact that physical, chemical, and biological processes are closely interrelated in determining the ecology of a pond.

Monitored fish behaviour and health measures were a good reflection of the monitored environmental changes. DO declined at night-time and in the early mornings that usually evoked surface gasping, slack feed consumption, and an increase in stress response. These behavioural symptoms were highly associated with mortality peaks that were registered during period of excessive depletion of DO. Ammonia metalled especially that which correlates with high temperatures had a massive inhibitory effect on growth and exposure to gill irritation and disease. The shading associated with the turbidity decreased the efficiency with which foraging was performed, and it also explained the variation between the patterns of growth within each cycle of production. These results confirm the susceptibility of fish health during both short-term and long-term changes of the environment, as sensor-based aquaculture literature has shown before.

The Gradient Boosted Decision Trees (GBDT) proved to be a good predictor in terms of the welfare risk classification and forecasting growth results (Sountharrajan et al., 2017). The accuracy and F1-scores were high and the regression output had low RMSE-values and high R 2-values and this confirmed the effectiveness of the model in addressing nonlinear and multivariate data. Among the most significant predictors, in terms of the feature importance rankings, there were the DO fluctuation and ammonia concentration, then turbidity and chlorophyll-a. The interpretation using SHAP also made it clear that combinations of high ammonia and low DO were the top predictors of the high-risk conditions, which is not easy to account for with the more traditional statistical means. These simulation outcomes confirm the usefulness of GBDT to include sensor derived variables in decision support systems.

The influence produced by management interventions, based on sensor monitoring, on the water quality and stability and fish performance, was detectable and measurable. Hourly dips in DO were reduced through optimised aeration schedules which subsequently helped in keeping physiological comfort intact and minimised mortality risk. Partial water exchange during optimum nutrient intervals reduced the build-up of ammonia and turbidity and enhanced visibility and increased plankton dynamics to a healthier part. Real-time monitoring with a feed optimization also led to a decrease of excess organic loading and feed conversion efficiency (Karpagam et al., 2021). Taken altogether, these interventions increased the sustainability of the environment and led to the steady increase in growth rates and better fish welfare. The effective implementation of the monitoring-directed policy supports the usefulness of the sensor-based system as an effective means of sustainable management of aquaculture.

Table 2: Water Quality Descriptive Statistics across Depths and Seasons

Parameter	Surface Layer (Mean ± SD)	Mid-Depth (Mean ± SD)	Bottom Layer (Mean ± SD)	Seasonal Trend Summary
Dissolved Oxygen (mg/L)	6.8 ± 1.2	5.4 ± 1.0	4.2 ± 0.9	Lowest during warm seasons; pronounced night-time dips
Ammonia (mg/L)	0.18 ± 0.05	0.26 ± 0.07	0.33 ± 0.09	Peaks after feeding; highest in post-monsoon period
Turbidity (NTU)	22 ± 4	28 ± 5	33 ± 6	Increases with nutrient build-up and phytoplankton growth
Temperature (°C)	28.5 ± 2.1	27.8 ± 1.9	27.3 ± 1.7	Elevated during pre-monsoon and summer months
Chlorophyll-a (µg/L)	18 ± 3	22 ± 4	26 ± 5	Peaks during nutrient-rich monsoon season

Future Research

Future directions ought to be directed towards the development of a superior monitoring structure through incorporation of the IoT-based, real-time sensor networks that have the capacity to transmit and store wireless data to the cloud (Uddin et al., 2022). On the one hand, the current research report equally proves the usefulness of non-networked systems, though, networked architectures would facilitate continuous remote monitoring as well as automated notifications of thresholds and more responsive management interventions. These systems have the potential of enabling scaled implementation of large aquaculture business and implementing centralised control of several ponds. Also, the use of sensor nodes that are energy-efficient and solar-powered data loggers would additionally make it more sustainable and make its operation in the long run viable.

The other potential opportunity is the use of state-of-the-art deep learning models to predict important parameters of water quality. Time series models like the Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCN) have more desirable characteristics in the temporal dependency and nonlinear dynamics of the DO progression and variation of ammonia and turbidity. By combining these models and using high-frequency data of sensor data, prediction of stresses or environmental instability can be made earlier and hence proactive interventions to avert negative effects on fish welfare. Incorporation of a combination of in-situ sensor monitoring and remote sensing instruments such as UAV or satellite imagery would also allow the large-scale examination of habitat state, nutrient loading trends and algal bloom animals and plants over broader aquaculture environments.

Lastly, new research must include more validation on various pond settings, species and production systems in order to enhance the overall validity of data-based models. Comparisons between cross-ponds and cross-species would assist predictive algorithms being refined and to identify universal stress predictors that can be used in wider aquaculture situations (Janaki & Geetha, 2017). An intelligent-software-based decision-support apparatus incorporating machine learning outcomes with mechanised manageable frameworks to aerate, exchange water, and distribute food may revolutionise the management framework by decreasing manual labour, lessening assets utilisation and increasing ecological robustness. All these improvements would add up to the creation of entirely intelligent, adaptive and sustainable aquaculture systems.

Acknowledgements

The authors wish to express their profound gratitude to the farm management team not only in making the aquaculture ponds available to them during the study but being supportive all through with regards to their operations. The results achieved so far have ensured the successful implementation and operation of the sensor-based monitoring system since technical personnel had to help in the installation of the sensors, calibration, regular servicing of the sensors, and data acquisition throughout the seasonal monitoring phases. The authors also consider the useful input of the members of the laboratories that considered the analysis of the plankton's samples, the evaluation of the sediment quality and the measurements of the nutrients that were necessary to comprehend the ecological dynamics of the ponds under study (Mohan et al., 2012). Lastly, the authors acknowledge their indebtedness to the supporting organisational bodies and funding authorities whose interest in enhancing environmental supervision and environmental sound aquaculture research studies made this work possible to be complete.

Conclusion

This paper illustrates that sensor-based surveillance would offer an efficient and feasible method of recording the dynamic physicochemical and habitat environment, which characterise fish welfare and yields in freshwater aquaculture ponds. The determination of high-resolution levels indicated that dissolved oxygen and ammonia variability played a crucial role in the responses to stress, feeding behaviour, growth suppression, and mortality risk factors, and seasonal nutrient build-up brought about the increase in turbidity and changes in the plankton structure. Gradient Boosted Decision Trees (GBDT) modeling has provided variability in DO, ammonia level, and turbidity as the most useful predictors of welfare and growth performance, which show the strength of using data as the basis of interpreting complex environmental interaction. Continuous monitoring informed management interventions including optimised aeration, focused water replacement and rebate of feeds resulted in significant improvements in water quality stability, improvement of growth rates and minimization of high-density effluent release. On the whole, the results validate the assertion that inexpensive, non-connected sensor systems, together with predictive analytics, provide a strong and expandable framework of encouraging healthy and sustainable aquaculture management.

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