Results in Chemistry 16 (2025) 102456

Contents lists available at ScienceDirect

Results in Chemistry

journal homepage: www.sciencedirect.com/journal/results-in-chemistry

Predictive modelling of aquaculture water quality using IoT and advanced machine learning algorithms

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ARTICLE INFO

Keywords:
Aquaculture
Tilapia
Water quality
IoT
Machine learning
Sustainable fisheries
Predictive modelling

ABSTRACT

Aquaculture plays a pivotal role in global food security, with tilapia (*Oreochromis niloticus*) being one of the most widely farmed species due to its resilience and productivity. However, maintaining optimal water quality remains a key challenge, particularly in rural aquaculture systems with limited access to real-time monitoring tools. This study presents a comprehensive six-month monitoring of key water quality parameters in tilapia ponds in Montería, Colombia, using a custom-built Internet of Things (IoT) system. The parameters monitored include pH, turbidity, temperature, and dissolved oxygen (DO)—critical indicators of aquatic health and fish productivity. Advanced machine learning models, including TensorFlow Neural Networks (TFN) and Aqua Enviro Index (AEI), were applied for predictive analysis. Results revealed a statistically significant regression model for temperature ($p < .001$) and a weak negative correlation between turbidity and temperature ($r = -0.093$), highlighting the complex interactions within tropical aquaculture systems. The study offers valuable insights into temporal water quality dynamics and supports data-driven water quality management in resource-constrained areas. Future applications may involve developing mobile dashboards for real-time farmer alerts and decision support, alongside localized training to enhance data literacy. These initiatives can significantly improve aquaculture sustainability, foster technological adoption, and contribute to global food security by empowering rural fish farming communities.

1. Introduction

Aquaculture has become one of the world's most rapidly expanding food production sectors, providing a primary source of animal protein for millions of people [1]. In particular, tilapia (*O. niloticus*) cultivation has been of significant importance in most nations due to its high growth rate, ability to tolerate extensive variations in environmental conditions, and huge market [2]. Yet, productivity and sustainability in aquaculture systems greatly rely on the water quality in which aquatic organisms are produced [3]. WQPs like temperature, DO, pH, and turbidity play pivotal roles in controlling the health and productivity of aquaculture systems [4,5]. Therefore, monitoring and controlling these parameters around the clock is essential to enhance fish health, growth, and overall sustainability in aquaculture systems [6].

Aquaculture system water quality can vary significantly depending on various factors, including season, human activity, and ecological changes [7]. The alteration in water quality can affect the metabolic processes, growth rate, and disease resistance of fish [8]. For instance, the metabolic rate and behavior of various fish species, such as tilapia are influenced by temperature, with tilapia having a preference for temperatures ranging from 25 °C to 30 °C. Exceeding this range can lead to stress, reduced growth rates, and disease susceptibility [9]. Technological advancements have witnessed the installation of real-time monitoring systems that make continuous records of critical water quality parameters. IoT is one technology that has been used to monitor water quality in various aquaculture systems [10]. IoT systems comprising sensors like digital thermometers, oxygen probes, portable pH meters, and turbidimeters enable continuous data acquisition. These systems facilitate on-the-spot water quality measurement, enabling instant intervention and controls to maintain optimal conditions for the growth of fish [11].

The information noted from IoT-enhanced sensors must undergo

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https://doi.org/10.1016/j.rechem.2025.102456
Received 6 May 2025; Accepted 16 June 2025
Available online 18 June 2025

rigorous preprocessing for its veracity and quality for further processing. Gaps in data, outliers, as well as irregularity in measurements can corrupt results and lead to misleading findings. Some data preprocessing techniques, such as imputation, normalization, and outlier detection, have to be employed to address these issues [12,13]. Once cleaned, the data can then be analyzed with statistical methods such as linear regression and correlation analysis to establish relationships between different water quality parameters and assess their effects on the health and productivity of fish [14,15]. Linear regression is a common statistical tool that relates independent variables (e.g., temperature, pH) [16] and a dependent variable (e.g., dissolved oxygen). Linear regression provides knowledge of the effect that the change in one parameter has on others and can be applied to predict future water quality patterns from previous records [17]. Correlation analysis, such as Pearson's correlation, also supports this observation by quantifying the direction and magnitude of the relationship among several variables [18]. Aside from these traditional methods, machine learning models have also emerged as effective tools for water quality prediction. Use of neural networks, namely TFN, facilitates the use of complex, multivariable data and helps enhance the accuracy of prediction [19]. Machine learning models, such as the TFN model, facilitate the analysis of large, high-dimensional datasets by extracting spatial and temporal patterns in real-time [20]. This approach is better at capturing interdependencies among water quality parameters since it can model non-linear interdependencies that are not detectable by conventional statistical methods [21]. Using advanced machine learning models like TFN is effective in modelling water quality parameters in aquaculture systems [22]. These models also help to assess the long-term sustainability of aquaculture systems by providing insight into how changes in environmental conditions can affect water quality and fish health in the long run.

Real-time monitoring and predictive modelling of water quality parameters not only support aquaculture management practices but also enhance sustainability [23]. By maintaining optimal conditions for fish growth, aquaculture producers can maximize productivity with minimum environmental impact [24]. Furthermore, real-time monitoring can help in early detection of likely issues such as oxygen deficiency, anomalous turbidity, or toxic pH fluctuations, enabling intervention promptly [25]. In response, developing more sophisticated models for water quality estimation and prediction is necessary to advance with aquaculture system sustainability, particularly in tropical nations such as Montería, Colombia, where tilapia aquaculture is a key driver of local economies.

In modern aquaculture, maintaining optimal water quality is crucial for ensuring healthy fish growth and sustainable production [26]. Environmental chemistry plays a vital role in understanding and managing the complex interactions of chemical parameters such as dissolved oxygen, pH, ammonia, nitrites, and heavy metals in aquaculture ponds [27]. Integrating Internet of Things (IoT) technology into pond management offers a powerful solution for real-time monitoring and control of these water quality parameters [28]. Using IoT-enabled sensors and wireless communication systems, farmers can continuously track environmental conditions, receive instant alerts about potential hazards, and automate interventions such as aeration or water exchange [29]. This smart monitoring approach not only improves fish health and productivity but also enhances environmental sustainability by reducing chemical imbalances and minimizing resource waste in aquaculture ecosystems [6]. Consequently, the combination of environmental chemistry and IoT technologies is transforming traditional aquaculture into an intelligent, data-driven practice [30].

The objective of this research is to track water quality parameters in tilapia ponds in Montería, Colombia, through real-time monitoring supported by IoT sensors. Moreover, the paper addresses the application of machine learning techniques for predicting and modelling water quality parameter correlations to provide a better and improved tool for aquaculture management. Using linear regression, correlation analysis, and TFN models, this research adds to the rising body of knowledge on aquaculture sustainability improvement through enhanced water quality monitoring and predictive modelling.

2. Materials and methods

This section summarizes the materials and methods used in this study, including the data collection process, software packages, statistical techniques, and model evaluation techniques used for WQP analysis in aquaculture systems.

2.1. Data collection and study area

The study was conducted in Montería, Colombia (January to June 2024), on tilapia (*O. niloticus*) aquaculture ponds. The data was obtained with an IoT system that continuously recorded the major water quality parameters, i.e., temperature, DO, pH, and turbidity. Temperature was recorded with digital thermometers, DO with an oxygen probe, pH with a portable pH meter, and turbidity with a turbidimeter. These parameters are quite significant in tilapia culture for maintaining healthy conditions [31], and they provide information on the environmental factors influencing aquaculture systems in Montería [32].

2.2. Data preprocessing and cleaning

The dataset obtained from the tilapia aquaculture ponds in Montería underwent several preprocessing steps to ensure its quality and readiness for further analysis. As is common with sensor-derived data, challenges such as missing values, outliers, noise, and unbalanced distributions were observed. To address these, a systematic cleaning and preprocessing protocol was implemented.

Normalization was then applied to bring all features onto a common scale, enabling meaningful comparisons across variables. Specifically, min-max scaling was used to rescale the data between 0 and 1, which is especially important for models sensitive to the magnitude of input values. Outliers were detected using both statistical methods such as the interquartile range (IQR) and z-score analysis, and context-based domain knowledge [33]. For instance, dissolved oxygen values falling beyond ± 3 standard deviations or exhibiting biologically implausible readings were flagged for further inspection [34]. Depending on their influence, these outliers were either corrected or removed to avoid skewing the analysis.

2.3. Software and tools

The analysis was performed using two popular software platforms: RStudio (version 4.3.2) and Python (version 3.13). RStudio was utilized for statistical analysis, including the calculation of correlation matrices and linear regression modelling, and to produce various visualizations. R packages such as ggplot2, stats, and cord were employed to simplify these analyses. Python was also utilized for additional statistical analysis and machine learning. Libraries like Numpy and Pandas were used to carry out mathematical operations and data manipulation, while Scipy was used for the computation of Pearson correlation coefficients. Seaborn was used for variable relationship visualization, and Scikit-learn was used for model implementation of linear regression as well as model validation.

2.4. Statistical methods

Some statistical procedures were employed to evaluate the interrelation among the parameters of water quality. Linear regression analysis was employed to measure the effect of independent variables, i.e., temperature and pH, on the dependent variable, i.e., Pearson's correlation, was employed to establish the strength and direction of linear relations among different WQPs. A Pearson correlation matrix was obtained to portray these relations and examine potential associations between parameters.

2.5. Adaptive ensemble integration and 3D multivariable prediction modelling

To enhance the robustness and accuracy of our predictive analysis, we employed an AEI approach combined with 3D multivariable prediction modelling. The AEI method involves the dynamic combination of multiple base learners—specifically, decision trees, support vector machines, and gradient boosting regressors—through a weighted ensemble strategy [35]. The weights for each learner are adaptively adjusted based on real-time performance metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) during cross-validation [36,37]. This ensures that the ensemble prioritizes models demonstrating higher predictive accuracy on the validation set.

For the 3D multivariable prediction model, we integrated three key dimensions of data: spatial (geographical coordinates), temporal (seasonal/time-based factors), and environmental (physicochemical parameters such as temperature, pH, DO, Turbidity). These variables were fed into a multilayer perceptron (MLP) neural network configured with three hidden layers using ReLU activation and a final linear output layer. Input features were normalized using min-max scaling to ensure comparability across scales, and data were split into training (70 %), validation (15 %), and test (15 %) subsets [38].

2.6. Model evaluation and index construction

To evaluate the performance and reliability of the predictive models, a set of widely accepted statistical metrics was employed. Specifically, R-squared (R^2) and *p*-values were used to assess the goodness-of-fit and statistical significance of individual predictors in traditional regression models (Fig. 1). These metrics quantified the proportion of variance in the dependent variable explained by the model.

The R-squared is calculated as [39]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y})^2}$$

Where, y_i = actual value, $\widehat{y}_i$ = predicted value, $\overline{y}$ = mean of actual values, n = number of observations.

To evaluate the model prediction accuracy, we computed RMSE and MAE as follows [40]:

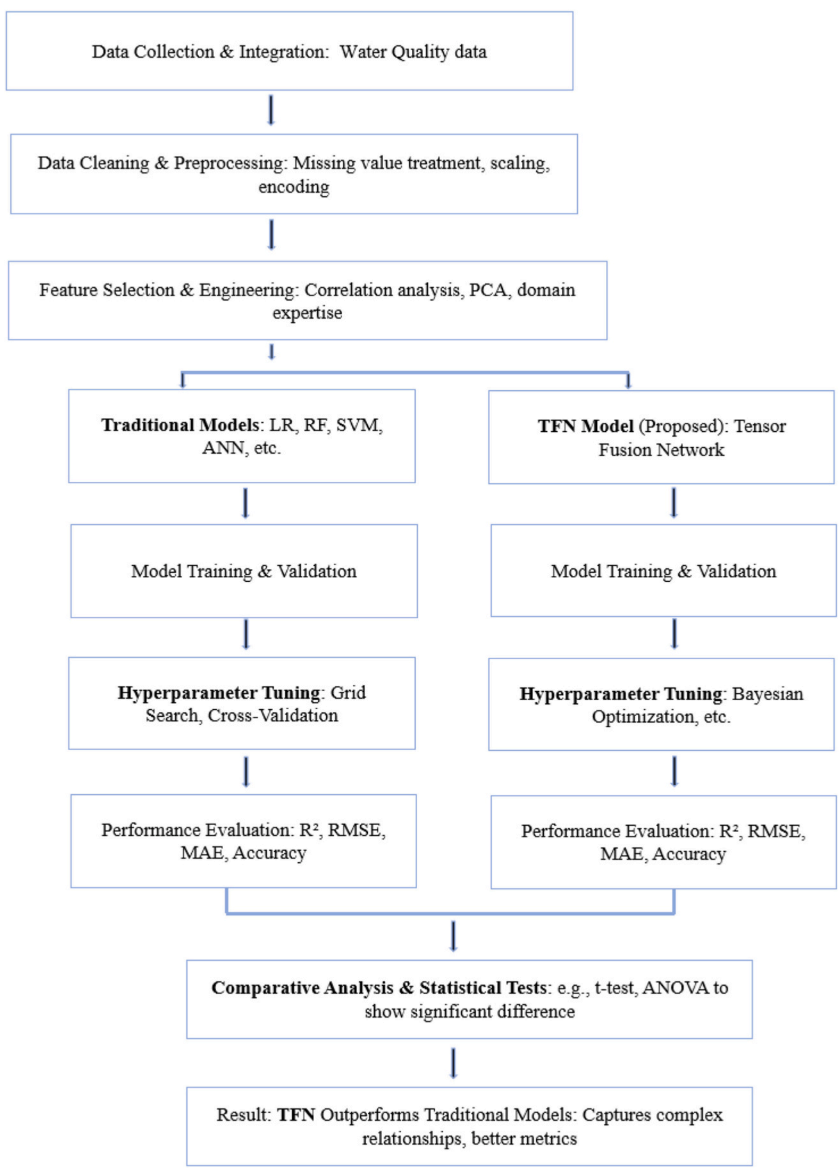


Fig. 1. End-to-End Predictive Modelling Pipeline for Environmental Data: Comparative Analysis of Traditional Models vs. TFN.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

For modelling non-linear relationships and improving predictive performance, a Neural Network model was implemented using TensorFlow. The model architecture included an input layer (equal to the number of features), one or more hidden layers with ReLU activation functions, and an output layer suited for regression. The forward propagation for one hidden layer can be represented as:

$$\hat{y} = f(W_2 \cdot ReLU(W_1 \cdot X + b_1) + b_2)$$

where, $\hat{y}$ = input feature vector; W_1, W_2 = weight matrices; b_1, b_2 = bias terms; ReLU (z) = max (0, z); f = identity function (for regression).

TFN model and the AEI represent fundamentally different approaches to environmental data interpretation. The TFN model is a machine learning-based analytical framework designed to learn from historical and real-time data for predictive modelling and pattern recognition. In environmental and aquaculture research, TFN models are employed to forecast dynamic parameters, identify anomalies, and support data-driven decision-making through algorithmic training. In contrast, the AEI is a static, composite index that integrates multiple physicochemical water quality parameters—such as dissolved oxygen, temperature, pH, turbidity, and nutrient levels—into a single quantifiable value. The AEI serves primarily as an evaluative tool, offering a summary assessment of environmental quality based on predetermined thresholds or scoring systems. While the AEI provides a straightforward interpretation of aquatic ecosystem status, it lacks predictive capacity. Therefore, the TFN model differs from AEI in its methodological foundation, functionality, and application—serving as a flexible computational model rather than a fixed environmental indicator.

3. Results

WQPs are essential in defining the health and stability of aquatic ecosystems, including aquaculture systems. For *O. niloticus* pond aquaculture, several of the major parameters are relevant to offer the optimal conditions for fish growth and survival. Temperature (°C) is significant because it influences the metabolic rate and behavior of fish. The optimal range of temperature for *O. niloticus* varies between 25 °C and 30 °C, with variation from this range possibly causing stress, reduced growth rates, and disease susceptibility. Dissolved Oxygen (DO, mg/L) is also an essential parameter because oxygen is used in fish respiration and general health. Optimum DO is a level of 5–9 mg/L, but below 4 mg/L can lead to hypoxia, which is detrimental to fish health, while above 10 mg/L may be an indication of water quality (Table 1) (Fig. 2). pH refers to the water's acidity or alkalinity, and a pH value of 6.5–8.5 is required by *O. niloticus*. Extreme pH levels can interfere with metabolic processes, prevent nutrient uptake, and induce disease. Lastly, turbidity (NTU) measures water clarity, which is defined by suspended matter. High turbidity can restrict light penetration, affect photosynthesis in aquatic plants, and stress the fish by impairing their gill function and feeding behavior. Monthly mean values of the given parameters and their standard deviations, as reported in the following table, can offer information about water quality changes in time. Aquaculture producers can measure these parameters to control safe and productive conditions for *O. niloticus* and accordingly make the right modifications to secure ideal fish health, growth, and system sustainability.

Table 1
Monthly Average Values of Water Quality Parameters with Standard Deviations.

Parameters	Jan	Feb	Mar	Apr	May	Jun
Temperature	27.29 ± 0.112	27.35 ± 0.106	27.31 ± 0.103	27.30 ± 0.133	27.20 ± 0.093	27.24 ± 0.151
DO	6.89 ± 0.106	6.87 ± 0.100	6.877 ± 0.138	6.88 ± 0.112	6.91 ± 0.116	6.91 ± 0.108
pH	7.83 ± 0.004	7.82 ± 0.029	7.82 ± 0.045	7.82 ± 0.039	7.83 ± 0.038	7.83 ± 0.086
Turbidity	3.33 ± 0.099	3.32 ± 0.087	3.31 ± 0.088	3.30 ± 0.093	3.32 ± 0.081	3.33 ± 0.09

Note: The table shows monthly averages of Temperature (°C), Dissolved Oxygen (DO, mg/L), pH, and Turbidity (NTU) from January to June. Values are presented as mean ± standard deviation for each parameter.

The linear regression results indicate a statistically significant but very slight **decline in water temperature over time**, as reflected by the negative slope (B = −0.00040, p = .018). Although the trend is statistically significant, the **effect size is small**; meaning the **rate of temperature decrease is minimal per time unit**. The model explains only **3.1 % of the total variation in temperature** (R^2 = 0.031) (Table 2), suggesting that other unmeasured factors are likely influencing water temperature more substantially.

In contrast**, no significant temporal change** was observed for **pH** levels (B = 0.000077, p = .272), indicating that pH remained relatively stable over the study period. The model's explanatory power for pH was also minimal, accounting for just **0.7 % of the variance** (R^2 = 0.007) (Table 3). This implies that **temporal factors had negligible influence on pH,** and variability in pH is likely due to spatial or environmental factors not captured by time alone.

The provided plot is a pairwise scatter plot matrix illustrating the correlation between four water quality parameters: temperature, pH, DO, and turbidity. The matrix consists of diagonal and off-diagonal elements. The diagonal elements provide kernel density plots of each parameter, temperature with a peak at 27.4 °C, pH with a concentration of 7.8, dissolved oxygen with a peak of 6.8 mg/L, and turbidity with a peak around 3.4 NTU. These density plots show information regarding the distribution of all variables (**Fig. 3**).

The off-diagonal entries of the scatterplot matrix illustrate pairwise relationships among water quality parameters, with each plot containing correlation coefficients (Corr) that quantify the linear strength and direction of associations. The analysis revealed predominantly weak linear relationships between variables. Temperature showed a weak negative correlation with pH (Corr = −0.114), dissolved oxygen (Corr = −0.028), and turbidity (Corr = −0.093), indicating that increases in temperature are associated with slight decreases in these parameters, although the strength of these relationships is minimal. Similarly, pH exhibited very weak positive correlations with dissolved oxygen (Corr = 0.052) and turbidity (Corr = 0.020), while dissolved oxygen and turbidity had a weak positive correlation (Corr = 0.101).

These low-magnitude correlation values (close to zero) suggest that the water quality parameters do not exhibit strong linear dependencies on each other. The implications of this finding are significant for interpreting water quality dynamics: each parameter appears to vary independently under the observed conditions, and no single parameter can be used as a reliable predictor of other using simple linear models. This independence may be due to complex environmental interactions, localized influences, or nonlinear dynamics that are not captured by pairwise correlation alone. Therefore, for more accurate analysis or predictive modelling, multivariate or nonlinear approaches may be more appropriate.

This heatmap illustrates the Pearson correlation coefficients among four water quality parameters: Temperature, pH, Dissolved Oxygen, and Turbidity. The correlation values range from −1 to 1, with negative values (red) indicating an inverse relationship between variables, and positive values (green) are indicating a direct relationship. Values near 0 (white) suggest little to no correlation between the parameters (**Fig. 4**).

These four key parameters—temperature, DO, turbidity, and pH—are selected to reflect the ecological status of the aquatic system and its suitability for drinking, recreation, and aquatic life. Their relative importance is represented through a weighting system, as shown in Table 1.

3.1. Aqua-Enviro index (AEI)

The Aqua Enviro Index (AEI) is a composite water quality indicator designed to integrate multiple environmental parameters into a single, interpretable metric that reflects the overall health of aquatic environments—especially in aquaculture systems. In this study, AEI was formulated using four critical water quality parameters: temperature, DO, turbidity, and pH. These parameters were continuously monitored in real-time using IoT-enabled sensors to capture spatiotemporal variations and detect potential stressors affecting aquatic life (Fig. 5).

The AEI transforms raw sensor data into standardized scores (0–1 scale) based on defined optimal thresholds for each parameter. The normalized scores are then aggregated using a weighted or unweighted mean to generate the AEI value, where higher AEI values indicate more favorable water quality conditions.

Algorithm 1. Aqua-Enviro Index.

```
Input:
  T  = Measured Temperature
  DO = Measured Dissolved Oxygen
  TU = Measured Turbidity
  PH = Measured pH

  T_opt_range  = [T_min, T_max]
  DO_opt_range = [DO_min, DO_max]
  TU_opt_range = [TU_min, TU_max]
  PH_opt_range = [PH_min, PH_max]

  Optional: Weights (w_T, w_DO, w_TU, w_PH) such that w_T + w_DO + w_TU + w_PH = 1

Function normalize(value, min_val, max_val):
  If value < min_val: return 0
  If value > max_val: return 0
  return (value - min_val) / (max_val - min_val)

Process:
  T_norm  = normalize(T, T_min, T_max)
  DO_norm = normalize(DO, DO_min, DO_max)
  TU_norm = 1 - normalize(TU, TU_min, TU_max)   # inverse, since higher turbidity = worse
  PH_norm = normalize(PH, PH_min, PH_max)

  AEI = (w_T * T_norm) + (w_DO * DO_norm) + (w_TU * TU_norm) + (w_PH * PH_norm)

Output:
  AEI ∈ [0,1], where:
    - AEI ≈ 1 → Excellent water quality
    - AEI ≈ 0 → Poor water quality
```

3.2. TFN-Based classification model for aquaculture

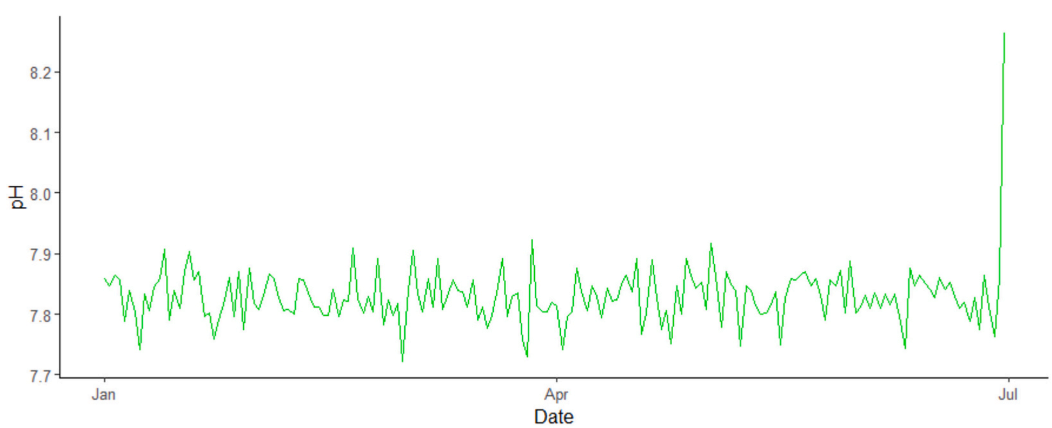
The TFN model intricately integrates real-time environmental and water quality information gathered from IoT sensors. The rich and high-dimensional dataset is a target of intense testing under an AEI, guaranteeing precise labeling for further analysis. Fig. 6 shows the feature importance and influence on the TFN model output using SHAP (SHapley Additive exPlanations) summary plots. The four subplots likely represent different model runs or prediction targets. In each plot, clear relationships between the input features and the model's predictions are visible. Higher values of Turbidity (shown in red or pink) generally correspond to positive SHAP values, meaning they increase the model's predicted output. Lower Turbidity values (in blue) are linked with negative SHAP values, reducing the prediction. Similar trends are seen for pH, Dissolved Oxygen, and Temperature, where higher values lead to increases in the model's output and lower values lead to decreases.

In the bottom-left subplot, Temperature shows a wide range of SHAP values, suggesting it strongly affects the model's predictions (Fig. 6). In the same plot, high Turbidity values also have some of the highest SHAP values (up to about 0.25), indicating a strong positive effect on the prediction. The top-left plot highlights Turbidity as the most influential feature, followed by Dissolved Oxygen and pH, based on the spread of their SHAP values.

3.3. TFN Model architecture design, training, and evaluation

```python
# Define the TFN model architecture
model = tf.keras.Sequential()

# Input Layer
model.add(tf.keras.layers.InputLayer(input_shape=(X_train_scaled.shape[1],)))

# Hidden Layers
model.add(tf.keras.layers.Dense(64, activation='relu'))
model.add(tf.keras.layers.Dense(32, activation='relu'))

# Output Layer (assuming classification into multiple classes, use softmax)
model.add(tf.keras.layers.Dense(len(y.unique()), activation='softmax'))

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

```python
# Evaluate the model
test_loss, test_accuracy = model.evaluate(X_test_scaled, y_test)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")

# Generate predictions
y_pred = np.argmax(model.predict(X_test_scaled), axis=-1)

# Classification report
print(classification_report(y_test, y_pred))
```



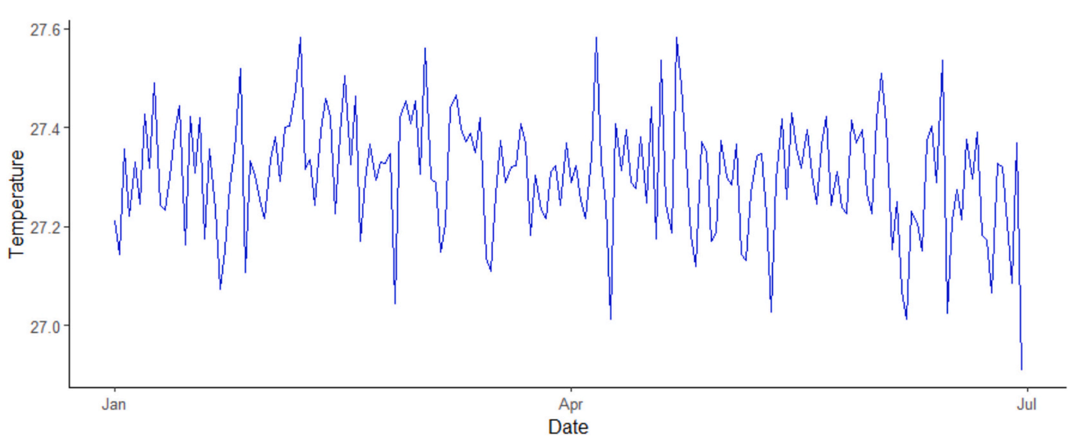


Fig. 2. Distribution of Monthly Data for Four WQPs in *O. niloticus* Pond Aquaculture Systems.

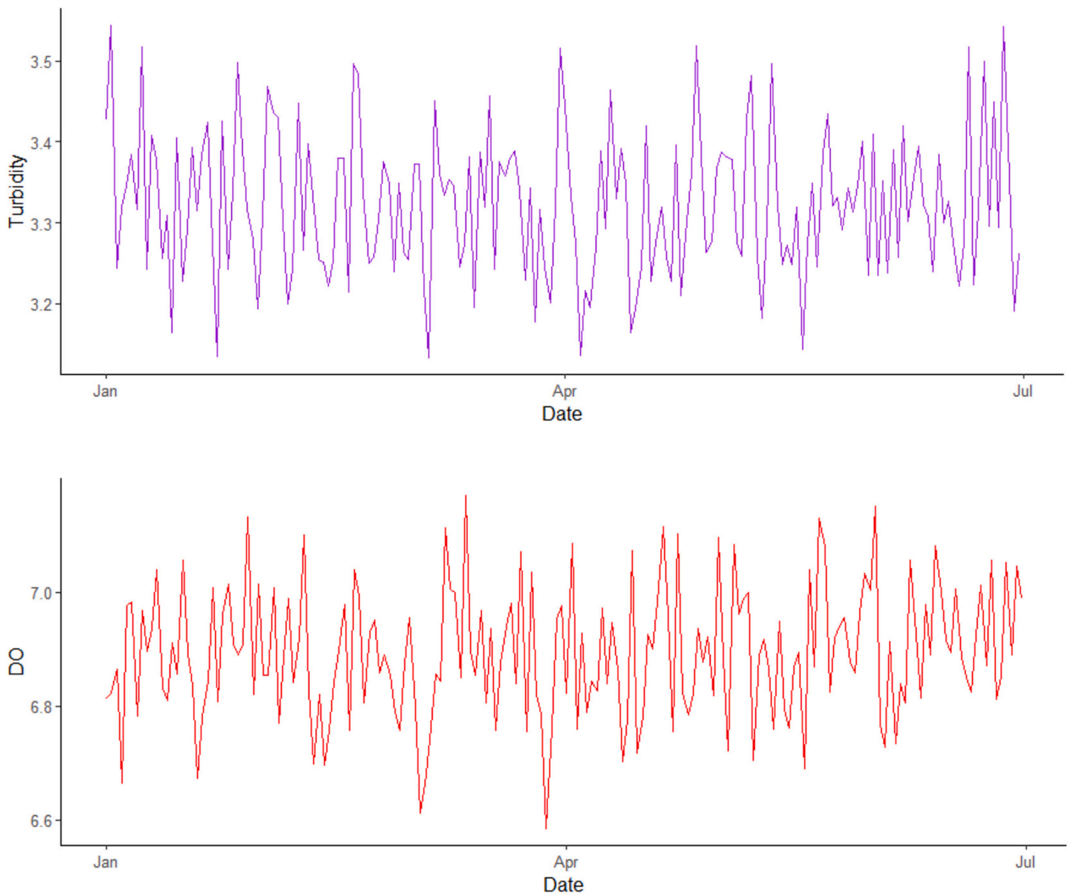


Fig. 2. (*continued*).

Table 2
Temporal Trends in Water Temperature: Results from Linear Regression Analysis.

Predictor	*B*	SE	*t*	*p*
Intercept	35.30	3.34	10.57	< 0.001***
Date	−0.00040	0.00017	−2.39	0.018*

Note: B = unstandardized regression coefficient; SE = standard error; t = t-statistic; p = p-value. $R^2 = 0.031$, Adjusted $R^2 = 0.025$, $F\,(1, 180) = 5.73$, $p = .018$. R^2 represents the proportion of variance in temperature explained by the model. Significance levels: $***p < .001$, $*p < .01$, $p < .05$.

Table 3
Temporal Trends in Water pH: Results from Linear Regression Analysis.

Predictor	B	SE	t	P
Intercept	6.305	1.384	4.56	< 0.001***
Date	0.000077	0.000070	1.10	0.272

Note: $R^2 = 0.007$, Adjusted $R^2 = 0.001$, $F\,(1, 180) = 1.21$, $p = .272$; Significance codes: $***p < .001$, $*p < .01$, $p < .05$.

The mathematical structure of the TFN model, as evident from the equations below, integrates 3D multivariable prediction techniques (Fig. 7), providing a holistic view of spatial and temporal dynamics. By analyzing the data in three dimensions, the model can identify interactions between various water quality parameters and environmental variables, achieving optimal prediction accuracy and robustness. It is precisely this multivariable strategy that can identify suitably complex temporal trends and spatial patterns, enabling real-time, trusted forecasts of water quality.

The TFN model was used to predict key physicochemical water quality parameters—temperature, DO, pH, and turbidity. Model accuracy was evaluated using the coefficient of determination (R^2), RMSE, and MAE. The TFN model demonstrated robust predictive capability across all parameters, achieving R^2 values above 0.82. Notably, the model exhibited the highest accuracy for turbidity prediction ($R^2 = 0.853$), followed closely by pH ($R^2 = 0.848$). The relatively low RMSE and MAE values across all parameters confirm the model's effectiveness in minimizing prediction errors. All error metrics are expressed in the respective units of the target parameters (Table 5). The low MAE value indicates that, on average, the predicted temperature values deviated from the actual measurements by only 0.038 °C. This high level of accuracy is particularly significant for aquaculture management, as water temperature directly affects fish metabolism, growth rates, oxygen availability, and overall health. Accurate temperature predictions support better-informed decisions regarding feeding schedules, aeration control, and disease prevention.

Fig. 7 shows four 3D scatter plots, each created from a separate model designed to predict one key water quality parameter: Temperature, DO, pH, and Turbidity. In each plot, the three axes represent the other three water quality parameters used as inputs. The color of each point shows the predicted value of the target parameter, as explained by the color bar next to each plot.

For example, the "Temperature Prediction Model" uses DO, pH, and Turbidity to predict temperature. These 3D plots help visualize how the water quality parameters are related to each other (Fig. 7). The way the points are spread out and the color changes across the plots show how changes in the input values affect the predicted results.

Algorithm 2. Training a TFN Model for Water Quality Classification.

1. Import Libraries:
•tensorflow, numpy, pandas, sklearn, matplotlib.

2. Load and Preprocess Data:
Load dataset:
Select features X and target y.
Split data into training and testing sets: X_train, X_test, y_train, y_test = train_test_split(X, y).
Scale features using StandardScaler.

3. Define TFN Model:
Input: Dense layer with input shape of features.
Hidden layers: 2 Dense layers (e.g., 64 and 32 units, ReLU activation).
Output: Dense layer with units = number of classes (softmax activation).
Compile model with Adam optimizer and sparse categorical crossentropy loss.

4. Train Model:
Use model.fit(X_train_scaled, y_train, epochs=50, batch_size=32, validation_data=(X_test_scaled, y_test)).

5. Evaluate Model:
Evaluate test accuracy: test_loss, test_accuracy = model.evaluate(X_test_scaled, y_test).
Make predictions and generate classification report.

6. Visualize Training Process:
Plot training and validation accuracy/loss curves.

4. Discussion

The findings of this study highlight the critical need for real-time monitoring and advanced analytical techniques in evaluating water quality within aquaculture systems. The deployment of IoT-based sensors enabled continuous and efficient observation of key parameters—temperature, DO, pH, and turbidity—in tilapia ponds [43]. These parameters exhibited both seasonal and temporal fluctuations, which directly influence the growth, survival, and overall productivity of *O. niloticus* [9,44]. Notably, temperature was found to significantly impact DO levels, reaffirming prior evidence that warmer water holds less oxygen, potentially leading to hypoxic conditions harmful to fish health [45]. PH values also varied across monitoring points, with observations suggesting that slightly alkaline conditions support more stable DO levels. This supports the recommendation by Jokinen (2024) [46], who indicated that a pH range of 6.5–8.5 is optimal for fish growth

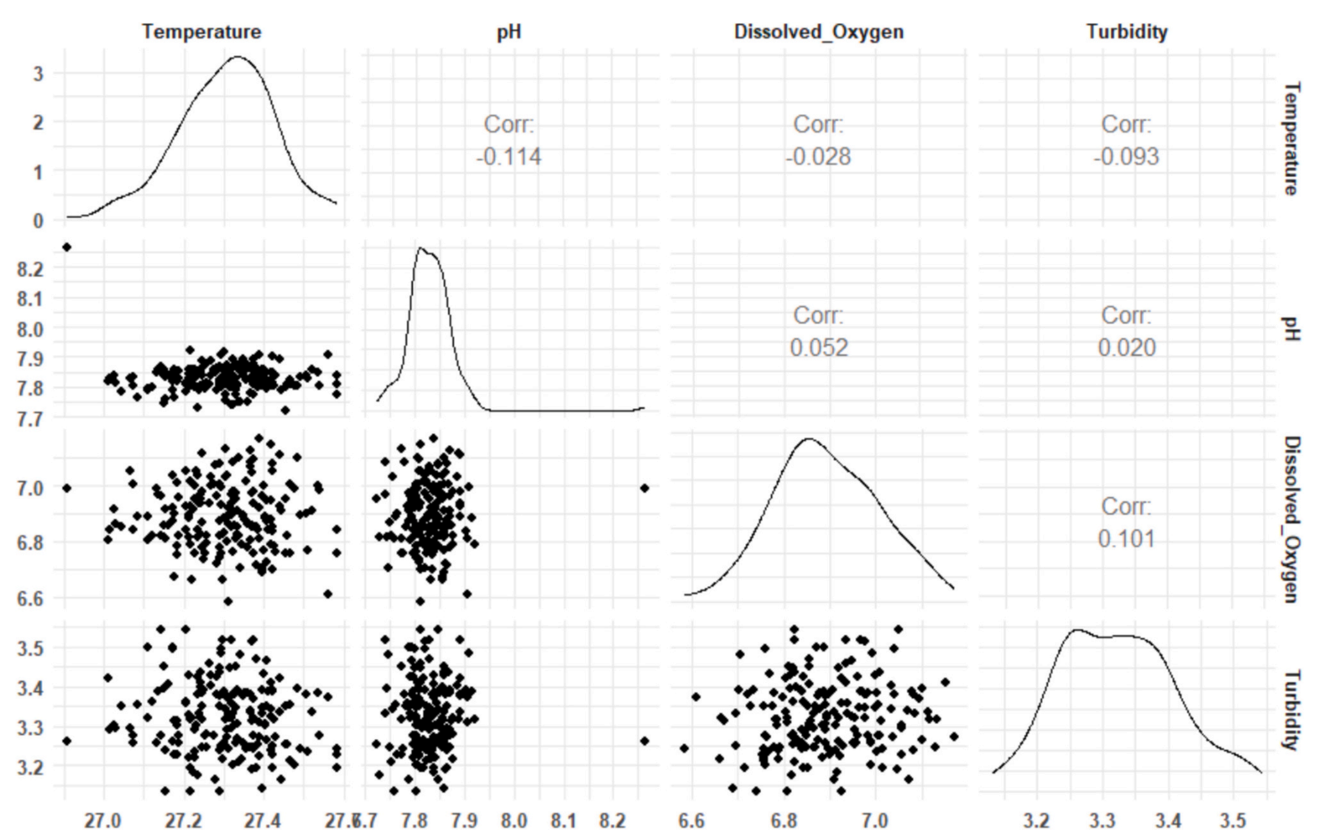


Fig. 3. Correlation Matrix of Physicochemical Parameters.

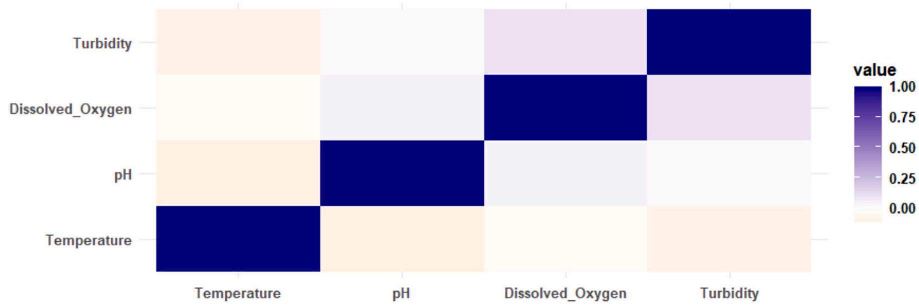


Fig. 4. The Pearson Correlation Matrix of Key Water Quality Parameters.

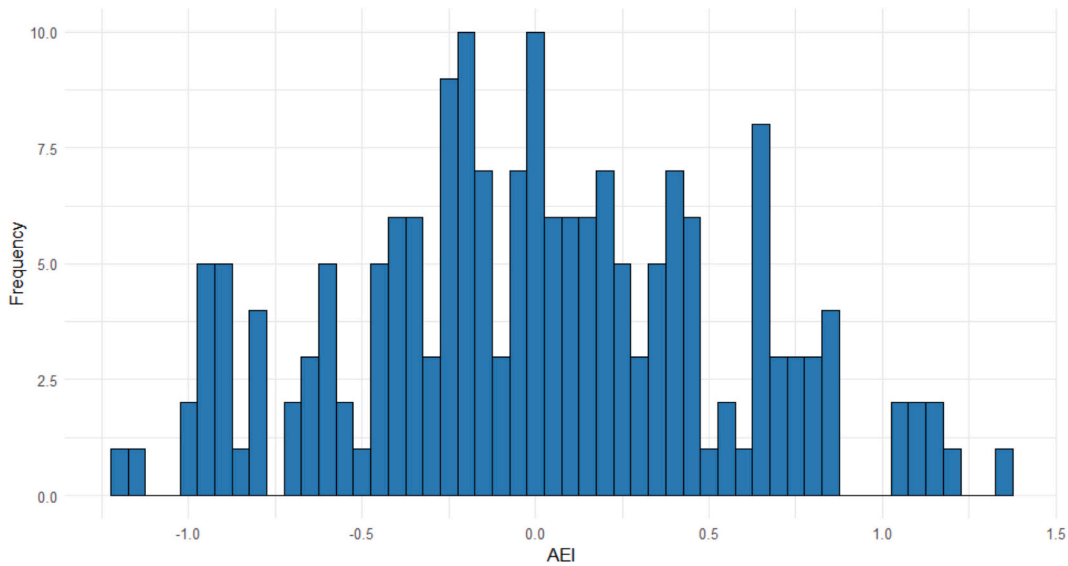


Fig. 5. Distribution of AEI.

and metabolic efficiency. Turbidity fluctuations, potentially driven by rainfall and sediment input were observed to influence photosynthetic activity and oxygen dynamics, as noted by Ravindran et al. (2022) [47].

Pairwise correlation analysis revealed generally weak linear relationships among the measured parameters, as depicted in Fig. 3. Temperature exhibited weak negative correlations with both pH and turbidity, while DO showed weak positive correlations with these variables. These results suggest limited direct linear interdependence among the parameters. However, interpreting these relationships requires caution, as natural aquatic systems are regulated by complex, often nonlinear processes. Therefore, linear correlation coefficients may not fully capture the intricate interactions among variables [48]. The lack of strong linear associations does not imply independence; rather, it indicates that these relationships might be modulated by additional environmental or seasonal drivers not addressed in this study.

Table 4 plays a pivotal role in linking scientific data with practical aquaculture management. By outlining threshold values for critical parameters—temperature, DO, pH, and turbidity—based on national standards, the table provides a reference framework for assessing pond or river conditions. These thresholds serve as early warning indicators for identifying suboptimal or hazardous conditions that could jeopardize fish health and productivity. Furthermore, the incorporation of a parameter-weighting system enhances decision-making by highlighting which variables most significantly influence overall water quality, especially in real-time monitoring contexts [49,50]. For instance, if DO levels fall below the recommended threshold, farmers can promptly initiate corrective actions such as aeration or adjusting stocking densities. As sensor technologies and access to open-source data platforms continue to evolve, integrating such frameworks into digital dashboards or mobile applications can significantly enhance precision aquaculture, particularly in resource-constrained environments [51,52].

Statistical analyses further revealed a strong negative correlation between temperature and DO, as well as a positive correlation between DO and pH. Regression modelling confirmed that temperature is a key predictor of DO levels, underscoring its importance in water quality regulation. These findings align with previous studies that emphasized the interconnectedness of water quality parameters in aquaculture systems [53,54]. Among the models tested, the TFN model exhibited the highest accuracy for DO prediction using multivariable inputs. Its capacity to capture nonlinear interactions and detect complex dependencies among parameters demonstrates its potential as a robust tool for aquaculture water quality management. This is particularly relevant in rapidly changing environments such as the Montería region, where seasonal variability and environmental stressors frequently impact pond conditions. According to Li et al. (2022) [22], machine learning models offer greater predictive precision compared to traditional methods [55]. Although the current study's model showed satisfactory performance based on standard evaluation metrics (R^2, RMSE, MAE), no direct comparisons with state-of-the-art models—such as Random Forest, XGBoost, or LSTM—were conducted (Table 6). Therefore, claims of

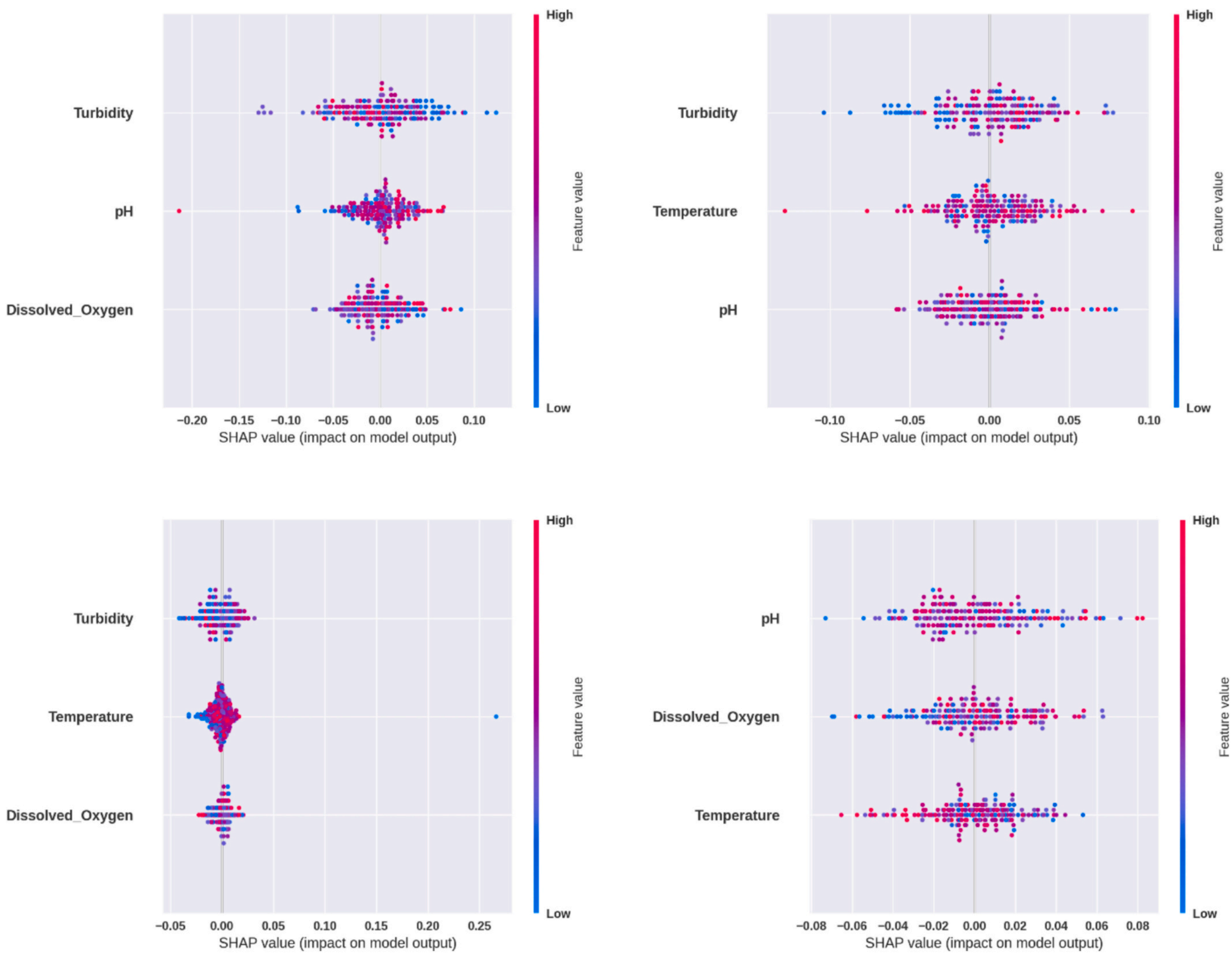


Fig. 6. Shap plots analysis of TFN model on a public dataset.

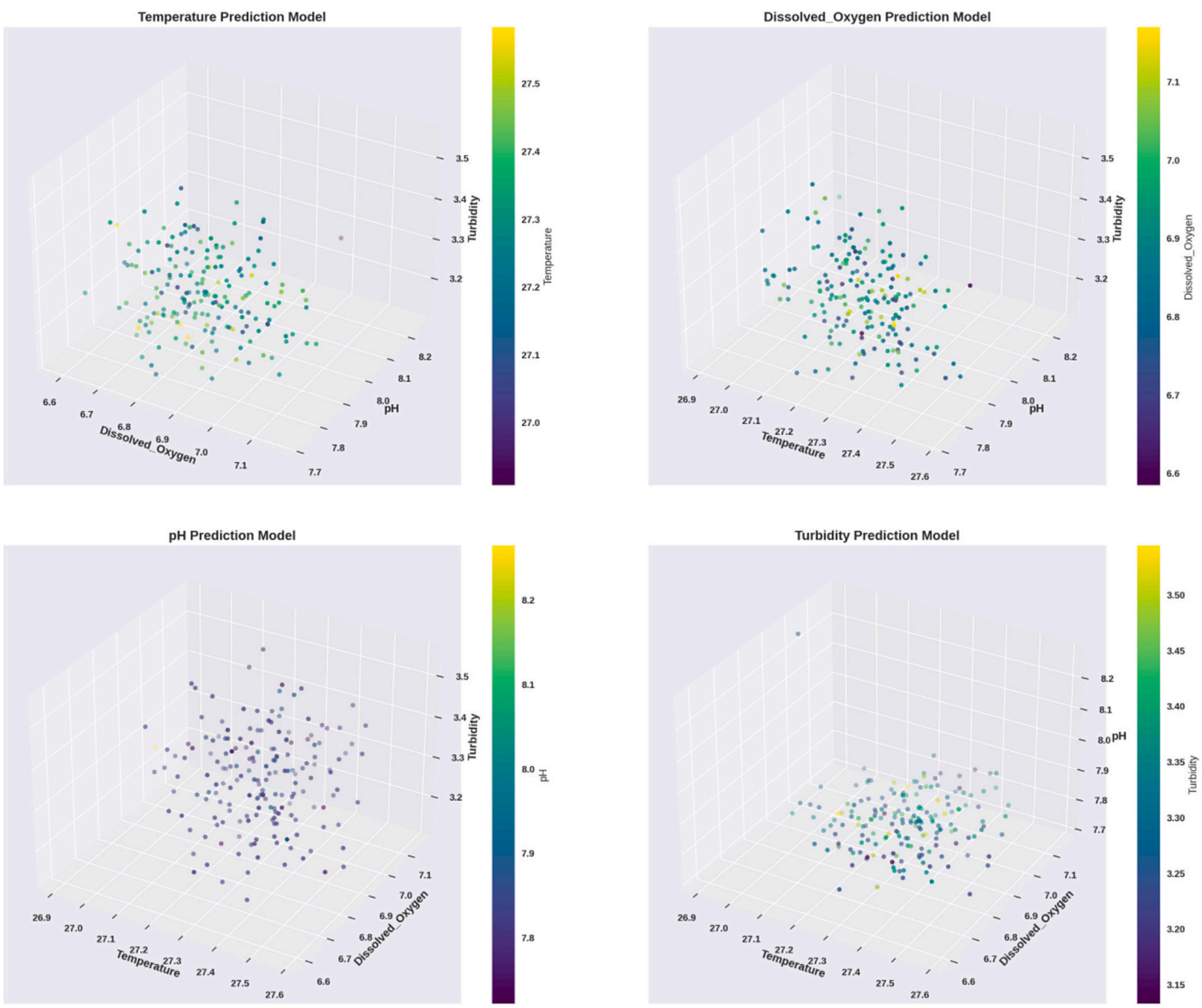


Fig. 7. 3D Visualization of Multivariable Prediction Models for Water Quality Parameters.

Table 4
The range of water and environmental variables for real-time and public datasets is provided by sources such as the Central Pollution Control Board (CPCB) 2019 and the Central Water Commission (CWC) 2022 [41,42].

Parameters	Desirable Range	Problematic Range	Weight for the real public dataset	Weight for real-time dataset
Temperature	20–25	< 15 or > 30	0.08	0.08
DO	6–9	<4 or > 10	0.10	0.20
Turbidity	0–5	>10	0.10	0.15
pH	6.5–8.5	<6 or > 9	0.12	0.15

enhanced predictive capacity should be interpreted cautiously. Future research should focus on comprehensive benchmarking against advanced machine learning algorithms to validate the generalizability and robustness of the proposed model across diverse datasets.

While integrating IoT and machine learning technologies shows strong promise for sustainable aquaculture management, several operational challenges remain. Issues such as sensor calibration errors can compromise data accuracy, leading to unreliable interpretations and ineffective interventions. Moreover, data drift—caused by sensor degradation, biofouling, or gradual environmental shifts—may negatively affect model performance if not regularly addressed. Seasonal variability also complicates model generalization, as models trained on data from one season may perform poorly in others. To enhance system reliability, future implementations should prioritize routine sensor maintenance, adopt adaptive model retraining strategies, and integrate seasonal trend adjustments. Collectively, these measures will help build more resilient and accurate water quality monitoring systems tailored for tropical aquaculture environments.

Table 5
TFN Model Evaluation Metrics for Target Water Quality Parameters.

Target Parameter	R^2 Score	RMSE	MAE
Temperature	0.846	0.047	0.038
DO	0.827	0.047	0.039
pH	0.848	0.019	0.013
Turbidity	0.853	0.034	0.028

Note: RMSE and MAE are in the respective units of each parameter.

Table 6
Comparative Summary of Machine Learning Techniques Used for Water Quality Prediction and Classification.

Author	Technique (s) Used	Best Model	Technique (s) Used	Results
Radhakrishnan and Pillai (2020) [56]	Support Vector Machine (SVM), Decision Tree, Naïve Bayes	Decision Tree Algorithm	Support Vector Machine (SVM), Decision Tree, Naïve Bayes	Accuracy = 98.50 %
Jain et al. (2021) [57]	Random Forest Algorithm, SVM, K-Nearest Neighbors (KNN)	Random Forest Algorithm	Random Forest Algorithm, SVM, K-Nearest Neighbors (KNN)	Accuracy = 92.127 %
Hmoud Al-Adhaileh and Waselallah Alsaade (2021) [58]	ANFIS, KNN, Feed-Forward Neural Network (FFNN)	ANFIS for WQI, FFNN for WQC	ANFIS, KNN, Feed-Forward Neural Network (FFNN)	ANFIS Accuracy = 96.17 %, FFNN Accuracy = 100 %
Malek et al. (2022) [59]	DT, Naïve Bayes, Gradient Boosting, KNN, ANN, RF, SVM	Gradient Boosting	DT, Naïve Bayes, Gradient Boosting, KNN, ANN, RF, SVM	Accuracy = 94.90 %
Khan et al. (2022) [60]	Principal Component Regression (PCR), Gradient Boosting Classifier (GBoost)	Gradient Boosting Classifier	Principal Component Regression (PCR), Gradient Boosting Classifier (GBoost)	PCR Accuracy = 95 %, GBoost Accuracy = 100 %
Aldhyani et al. (2020) [61]	NARNET, SVM, KNN, Naïve Bayes, LSTM	NARNET for WQI, SVM for WQC	NARNET, SVM, KNN, Naïve Bayes, LSTM	SVM Accuracy = 97.01 %, R^2 (NARNET) = 96.17
Khoi et al. (2022) [62]	AdaBoost, GBoost, HGBoost, LGBoost, XGBoost	Extreme Gradient Boosting (XGBoost)	AdaBoost, GBoost, HGBoost, LGBoost, XGBoost	R^2 = 0.989, RMSE = 0.107
This Study	TFN, Linear Regression, Random Forest	TFN Model	TFN, Linear Regression, Random Forest	R^2 = 0.846, RMSE = 0.047, MAE = 0.038
This Study	Linear Regression	Linear Regression	Linear Regression	R^2 = 0.025, F (1, 180) = 5.73, p = .018

5. Conclusion

This study demonstrates the effectiveness of an IoT-based water quality monitoring system in a tropical tilapia aquaculture environment in Montería, Colombia. Real-time measurement of key parameters—temperature, DO, pH, and turbidity—enabled continuous monitoring and dynamic analysis of environmental conditions. Notably, temperature showed a significant inverse correlation with DO, while pH and DO exhibited moderate positive associations, emphasizing the need to control these variables for optimal fish health and growth. The application of a TFN model further enhanced predictive capabilities, outperforming traditional regression models by capturing nonlinear interactions between parameters. These findings validate the potential of integrating IoT systems with advanced machine learning techniques for adaptive aquaculture management, especially in resource-constrained rural settings.

Looking forward, future applications may include the development of a user-friendly mobile dashboard to provide farmers with real-time alerts and decision-support tools. Additionally, capacity-building initiatives such as localized training programs and workshops can help fish farmers interpret data and implement responsive water quality management practices. These steps will not only promote the scalability of smart aquaculture technologies but also contribute meaningfully to sustainable fish production and global food security goals.

Ethics and Consent to Participate Declarations

Not applicable.

Clinical trial number

Internet of Things (IoT) devices and subsequent analysis using deep learning techniques. As such, clinical trial procedures do not apply to our work.

Consent to Publish Declaration

Not applicable.

Software Usage

Artificial intelligence (AI) software, including machine learning libraries such as TensorFlow, was utilized for data analysis and modelling in this study. While no AI tools were used to write or prepare the manuscript text, AI-assisted tools were employed solely to support ideation and conceptual thinking during the research process.

Third-party involvement

No persons or third-party services were involved in the research or manuscript preparation who are not listed as an author or acknowledged in the manuscript.

CRediT authorship contribution statement

Md. Abdullah Al Mamun Hridoy: Writing – review & editing, Writing – original draft, Visualization, Supervision, Software, Conceptualization. **Chiara Bordin:** Writing – review & editing, Writing – original draft. **Andleeb Masood:** Writing – review & editing. **Khalid Masood:** Writing – review & editing.

Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Md. Abdullah Al Mamun Hridoy reports Sylhet Agricultural University did not provide article publishing charges, statistical analysis, and writing assistance. Md. Abdullah Al Mamun Hridoy reports a relationship with Sylhet Agricultural University that includes: non-financial support. Md. Abdullah Al Mamun Hridoy has patent pending to no. No If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The author expresses sincere gratitude to the Mendeley Data repository for providing a platform to share and access the dataset, which greatly supported the development of this research.

Data availability

https://prod-dcd-datasets-cache-zipfiles.s3.eu-west-1.amazonaws.com/dgdr2kfbyt-1.zip

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