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Engineering assessment of water quality correlations for passive aquaponic systems in tropical environments

Jorge Saul Fandiño Pelayo[1], Luis Sebastian Mendoza Castellanos[2], Rocio Cazes Ortega[1], O. Lengerke[1]

[1] Department of Natural Sciences and Engineering, Unidades Tecnólogicas de Santander (UTS), Student Street 9-82, Bucaramanga, 680005, Colombia

[2] Department of Engineering, Universidad Autónoma de Bucaramanga (UNAB), Avenue 42 No. 48–11, Bucaramanga, 680005, Colombia

*Corresponding author E-mail: jfandino@correo.uts.edu.co

ABSTRACT

This study presents an engineering-oriented correlation analysis of water quality variables—pH, temperature, and dissolved oxygen (DO)—in a passive aquaponic system integrating red tilapia (*Oreochromis* spp.) and lettuce (*Lactuca sativa*) under tropical outdoor conditions. Environmental data were collected at 45-minute intervals over three months using embedded sensors and a microcontroller-based data logger. Pearson's r, Spearman's r_s, and Kendall's τ were applied to evaluate linear and monotonic relationships among variables. The results indicate a moderate, statistically significant positive correlation between pH and DO (Pearson's $r = 0.566, p < 0.001$), and a weaker but still significant positive correlation between temperature and DO (Pearson's $r = 0.420, p < 0.001$). The latter contrasts with the expected inverse trend in closed systems, suggesting compensatory biological processes in passive tropical environments. No significant relationship was found between pH and temperature (Pearson's $r = 0.081, p = 0.271$). These findings demonstrate that natural environmental dynamics can support acceptable water quality levels without active aeration or control systems. The correlation structure obtained may inform the design of low-cost, energy-efficient monitoring frameworks and decision-support tools for aquaponic systems in resource-constrained or off-grid environments.

Keywords: Passive aquaponics, water quality monitoring, pH, dissolved oxygen, temperature, sensor-based systems, correlation analysis, low-energy design, decision support

1. Introduction

Aquaponics is an integrated and sustainable agricultural system that combines aquaculture and hydroponics in a closed-loop cycle, where water and nutrients are continuously recirculated between fish and plant units [1], [2]. This approach reduces freshwater consumption and nutrient loss, offering a circular and resilient solution to global food and water challenges, particularly in areas affected by water scarcity and land degradation [3], [4]. It has been successfully implemented in both urban and peri-urban settings to meet growing demands for localized food production while minimizing environmental impact [5], [6].

A key determinant of system efficiency and biological performance in aquaponics is water quality. Critical parameters such as pH, dissolved oxygen (DO), and temperature affect plant nutrient uptake, fish respiration, and microbial nitrification [7], [8]. For instance, pH governs nutrient solubility and microbial efficiency, while DO availability supports aerobic respiration in fish and nitrifying bacteria [9], [10]. Temperature, in turn, influences both DO solubility and metabolic rates across species. Its regulation is therefore essential to avoid thermal stress or oxygen depletion [11], [12].

Although modern aquaponic systems increasingly incorporate Internet of Things (IoT) technologies for real-time monitoring and automation [13], [14], these solutions often rely on high-cost infrastructure and advanced technical support. This makes them impractical for small-scale or rural farmers, particularly in developing countries [15], [16]. In such contexts, low-intervention or passive aquaponic systems operated without active control or mechanical aeration are emerging as viable, low-cost alternatives [17], [18]. These systems depend heavily on natural balances and environmental dynamics, underscoring the need for improved understanding of variable interactions to support decision-making in the absence of automation.

Despite the ecological relevance of passive systems, most existing studies focus on controlled laboratory conditions, with limited emphasis on long-term, high-frequency field data from tropical outdoor settings [19], [20]. Moreover, few studies have applied comprehensive statistical methods such as correlation matrices, monotonic correlation analysis, or time-resolved comparisons to explore relationships between water quality variables under real-world conditions [21], [22]. Understanding these correlations is vital, as they can inform early warning mechanisms, guide manual interventions, or even serve as the basis for predictive algorithms in future low-cost digital systems [23].

2. Research method

2.1. Experimental Setup

The experimental trial was conducted in a closed recirculating aquaponic system with a floating bed configuration, located in the rural area of Barro Blanco, Piedecuesta, Santander, Colombia (7°01′N, 73°03′W; altitude: 1005 m). In this design, the hydroponic grow bed was positioned directly above the fish tank, forming a compact vertical layout. Water was recirculated between the aquatic and plant subsystems without external discharge, except for minimal replenishment due to evaporation. The site is characterized by a tropical climate, with daily temperatures typically ranging from 22 °C to 30 °C and moderate rainfall. The aquaponic unit consisted of a 1000-liter circular tank stocked with red tilapia (*Oreochromis* spp.) and a hydroponic bed supporting lettuce (*Lactuca sativa*) on floating polystyrene rafts.

Water circulation and basic aeration were maintained using a brushless DC submersible pump (rated 1000 L/h, 5 m head, 12 V/24 V). The pump transported water from the fish tank through a three-stage filtration system: (i) a coarse solids separator, (ii) a fine sediment trap, and (iii) a dual-chamber biofilter. From the biofilter, the water was delivered to the grow bed and subsequently returned to the fish tank via gravitational free-fall. This return path generated surface turbulence, enabling passive aeration without mechanical diffusers.

The entire system, including the pump and sensor array, was powered by a photovoltaic solar panel. Energy consumption was estimated based on two components: a 20 W brushless DC pump operating approximately 10 hours per day, and a 12 W Raspberry Pi 3 microcontroller running continuously. Together, these devices required around 488 Wh per day. Considering typical solar insolation in the region (5 peak sun hours) and standard efficiency losses (30%), a solar panel of at least 150 W was necessary to ensure stable off-grid operation.

Environmental monitoring was performed using three calibrated sensors: a digital thermometer (±0.5 °C accuracy), a galvanic-type dissolved oxygen sensor (±0.2 mg/L accuracy), and a glass electrode pH sensor (±0.1 pH unit accuracy). Data were recorded at 45-minute intervals over three months (March to May), yielding 2880 time-resolved observations per variable. Manual weekly calibration was conducted following FAO-recommended protocols for small-scale aquaponics [1].

Due to its critical role in biological performance, dissolved oxygen was continuously monitored [24].

2.2. Statistical Analysis

The statistical analysis was conducted in two phases: (1) evaluation of the normality of each variable, and (2) determination of the correlation strength between variable pairs. This procedure followed established methodological guidelines for water quality and environmental data [25].

To assess normality, two complementary tests were applied. The Shapiro–Wilk test evaluated whether each dataset conformed to a Gaussian distribution using order statistics, while the D'Agostino–Pearson omnibus test jointly assessed skewness and kurtosis. A significance level of $\alpha = 0.05$ was adopted for both tests. The outcomes informed the appropriate choice of correlation method for each pair of variables: temperature (T), pH, and dissolved oxygen (DO). Correlation analysis included Pearson's correlation coefficient (r), which quantifies linear associations and is computed as:

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{1}$$

To assess monotonic and ordinal relationships, Spearman's rank correlation coefficient (r_s) and Kendall's tau (τ) were also calculated. Spearman's coefficient is defined as:

$$r_s = 1 - \frac{\sum d_i^2}{n(n^2-1)} \tag{2}$$

where d_i denotes the rank difference of each observation pair. Kendall's tau measures the ratio of concordant to discordant pairs, expressed as:

$$\tau = \frac{(number\ of\ concordant\ pairs - number\ of\ discordant\ pairs)}{\frac{1}{2}n(n-1)} \tag{3}$$

Each correlation coefficient was calculated for the pairs (pH, DO), (T, DO), and (pH, T).

The strength of the relationships was interpreted following the classification proposed by Dancey and Reidy [25]: weak if $|r| < 0.3$, moderate if $0.3 \le |r| < 0.7$, and strong if $|r| \ge 0.7$. Statistical significance was determined at $p < 0.05$.

3. Results

3.1. Descriptive analysis of water quality variables

A total of 2880 time-resolved measurements were collected for each variable—pH, temperature, and dissolved oxygen (DO)—during the monitoring period from March to May. As shown in Figure 1, the empirical distributions of these variables were represented using histograms with kernel density estimations. The pH values ranged from 4.5 to 9.5, with a modal value around 6.8, indicating predominantly slightly acidic to neutral conditions. Temperature values fluctuated between 19.5 °C and 29.8 °C, clustering around 26 °C, which is consistent with typical tropical climate conditions. DO concentrations varied from 1.8 to 10.0 mg/L, with a high density of values between 5 and 7 mg/L, suggesting adequate oxygenation for aquaponic organisms under passive operation.

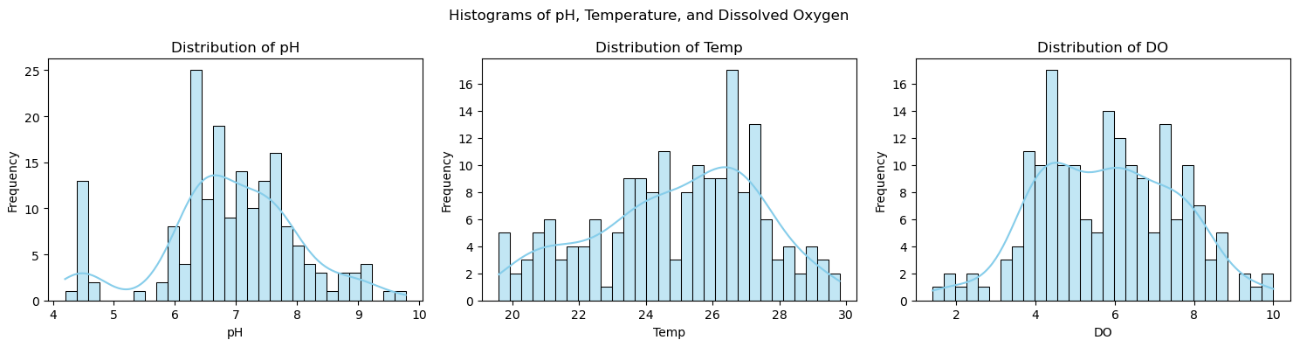

Figure 1. Distributions of pH, temperature, and dissolved oxygen levels; kernel density estimations illustrate the frequency and spread of each variable

3.2. Correlation matrix and pairwise relationships

As illustrated in Figure 2, the Pearson correlation matrix summarizes the linear associations among the three variables. A moderate and statistically significant positive correlation was observed between pH and DO (Pearson r = 0.566, $p < 0.001$), corroborated by Spearman's $r_s = 0.589$ and Kendall's $\tau = 0.426$ ($p < 0.001$ in both cases). This indicates that increases in pH tended to coincide with elevated DO levels.

Temperature and DO also exhibited a positive and statistically significant correlation, although of lesser magnitude (Pearson r = 0.421, $p < 0.001$; Spearman $r_s = 0.387$; Kendall $\tau = 0.271$). This trend contrasts with the inverse relationship typically reported in controlled or closed systems, where oxygen solubility decreases as water warms. In the present passive, outdoor configuration, compensatory mechanisms such as photosynthetic oxygen release and enhanced gas exchange at the water–air interface may offset thermal suppression of oxygen solubility [9], [11], [12]. This result highlights the importance of considering environmental dynamics when interpreting temperature–DO interactions in tropical aquaponic environments.

In contrast, the correlation between pH and temperature was weak and not statistically significant (Pearson r = 0.082, p = 0.2718), a finding reinforced by Spearman ($r_s = 0.118$, p = 0.1133) and Kendall ($\tau = 0.077$, p = 0.1251). This suggests that these variables operated independently during the study period.

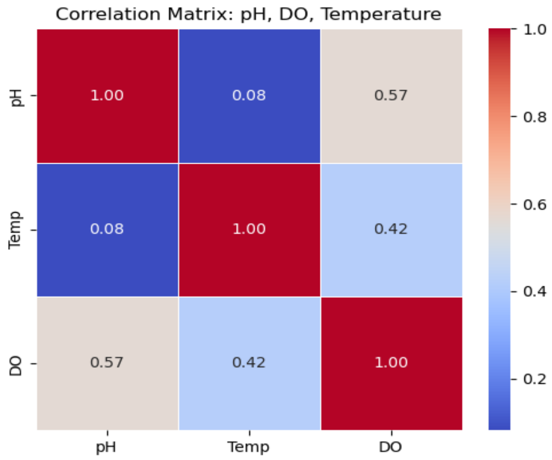

Figure 2. Pearson correlation matrix among water quality parameters; color scale indicates strength and direction of linear relationships

3.3. Scatter plot evaluation

Scatter plots with regression lines were generated to illustrate the relationships between the variable pairs (Figures 3–5). As shown in Figure 3, a clear positive trend between pH and DO is evident, confirming the statistical results.

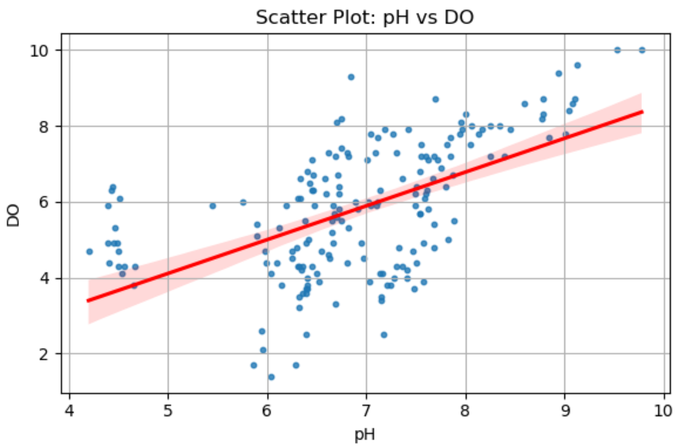

Figure 3. Scatter plot and regression line between pH and dissolved oxygen

This association, illustrated in Figure 3, may be attributed to photosynthetic activity and microbial processes that simultaneously increase pH and oxygen levels during daylight hours. As shown in Figure 4, the relationship between temperature and DO also exhibits a positive correlation. However, the data display greater dispersion, suggesting that additional environmental or biological factors may have influenced the variability.

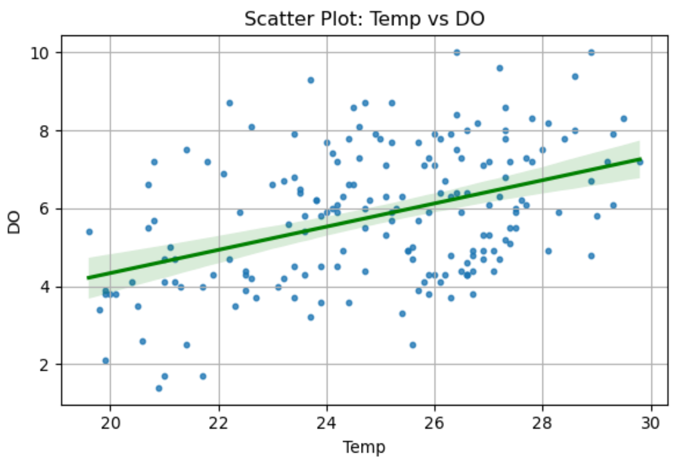

Figure 4. Scatter plot and regression line between temperature and dissolved oxygen

The scatter plot of pH and temperature in Figure 5 shows no discernible pattern, which is consistent with the absence of a statistically significant association.

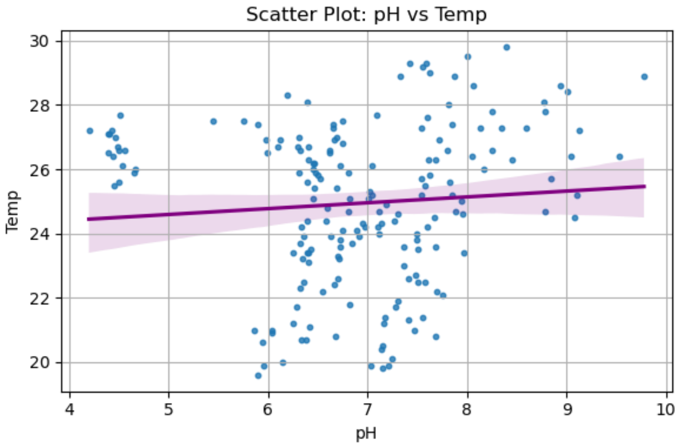

Figure 5. Scatter plot and regression line between pH and temperature

No significant outliers or anomalies were detected in the plots, confirming the integrity and consistency of the dataset throughout the monitoring period.

4. Discussion and conclusions

The results of this study demonstrate statistically significant correlations among key water quality parameters in a closed recirculating aquaponic system under tropical outdoor conditions. The moderate positive correlation between pH and dissolved oxygen (DO) ($r = 0.566$, $p < 0.001$) uggests that natural biological processes—such as microbial nitrification and photosynthesis—may jointly influence these variables. This observation aligns with previous findings indicating that aquatic photosynthetic organisms can elevate both pH and DO levels during daylight hours, particularly in low-intervention systems [9], [11].

The weaker but still significant correlation between temperature and DO ($r = 0.421$, $p < 0.001$) is notable. In controlled aquaculture systems, temperature usually shows a negative correlation with DO due to solubility limits. In contrast, the positive association found here likely reflects compensatory dynamics such as photosynthetic oxygenation and atmospheric exchange, which can offset solubility constraints in open, unshaded systems [11], [12]. This emphasizes the importance of site-specific data acquisition in tropical aquaponic settings, since extrapolations from temperate or indoor systems may be misleading.

The lack of correlation between pH and temperature confirms that these two parameters fluctuated independently. For system managers in low-resource contexts, this independence is useful: variations in pH cannot be assumed to reflect thermal stress, and vice versa. This reduces the risk of false alarms in monitoring protocols and supports the use of independent control thresholds.

These insights have direct implications for the design of low-cost aquaponic systems. In the absence of advanced automation, understanding statistically supported parameter relationships enables informed decision-making and proactive intervention with minimal sensor inputs. For instance, the coupling between pH and DO could support lightweight decision-support tools based on microcontrollers (e.g., Arduino, ESP32) integrated with cloud platforms such as Firebase. Such systems could also serve as a first step toward the gradual incorporation of artificial intelligence techniques, including anomaly detection and predictive modeling, without requiring high infrastructure investment.

From a sustainability perspective, the findings contribute to the development of aquaponic technologies that are energy-efficient, environmentally adaptive, and scalable across agroecological zones. Demonstrating the viability of a low-intervention system powered by solar energy and operating without mechanical aeration supports the goals of sustainable intensification and circular bioeconomy, particularly in areas with limited resources.

In conclusion, this study shows that pH and DO are moderately and positively correlated, temperature and DO also correlate positively in contrast to conventional expectations, and pH and temperature remain statistically independent. These findings not only demonstrate significant interrelationships among water quality variables but also provide practical insights for designing robust, low-maintenance aquaponic systems. Future work should test different biological loads, species combinations, and seasonal conditions, and explore how correlation-based indicators can be integrated into predictive control schemes and data-driven diagnostics.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

J.S. Fandiño Pelayo: conceptualization, experimental design, data analysis, and manuscript writing. R. Cazes Ortega: contribution to methodological development and support in analytical interpretation. L.S. Mendoza Castellanos: support in results interpretation and graphical data presentation. O. Lengerke: academic supervision and critical review of methodological consistency. All authors reviewed and approved the final version of the manuscript.

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