

Effects of continuous water monitoring on the productive performance of Tilapia

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Abstract

Daily fluctuations in temperature, pH, and turbidity drive stress, feed inefficiency, and mortality in small-scale aquaculture. Manual sampling (1–2 readings/day) fails to capture rapid parameter shifts. To overcome this, we designed a low-cost, open-source monitoring system using an embedded architecture, commercial sensors, wireless transmission, an HMI interface, and automated 5-minute logging. Its biological efficacy was validated over a 12-week trial in Nile tilapia (*Oreochromis niloticus*) culture in Pamplona, Colombia, comparing manual control and automated experimental groups (n = 3 tanks/treatment with equivalent stocking densities and feeding regimes). The automated system significantly reduced water quality variability and excursion durations outside optimal ranges, resulting in superior production outcomes. At harvest, fish in the automated treatment achieved greater final weight (115.67 ± 1.46 g vs. 102.10 ± 1.60 g; +13.3%), higher specific growth rate (SGR: $2.12 \pm 0.11\%/day$ vs. $1.85 \pm 0.14\%/day$), and improved feed conversion ratio (FCR: 1.31 ± 0.05 vs. 1.64 ± 0.02) ($p \leq 0.021$). Cumulative mortality was markedly reduced (4.3% vs. 11.7%), yielding higher final biomass. The system demonstrated high reliability (98.5% uptime) with no sensor drift, with power interruptions mitigated by backup solutions. These findings show that continuous, affordable monitoring stabilizes the culture environment, enhancing growth, feed efficiency, and survival. This replicable and scalable system provides a foundation for integrating additional parameters (e.g., dissolved oxygen, ammonium) and predictive analytics.

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1. Introduction

Aquaculture has established itself as one of the main pillars of global animal protein supply for human consumption and, in recent decades, its growth has outpaced that of capture fisheries [1], [2]. Alongside the sustained increase in demand, production systems have diversified across very different geographic and socioeconomic contexts, ranging from intensive and highly technological facilities to small-scale family operations with limited resources. In recent years, water quality management has consistently emerged as the bottleneck conditioning zootechnical performance, profitability, and resilience of production systems [3], [4].

Nile tilapia (*Oreochromis niloticus*), one of the most widely farmed species worldwide due to its hardiness and strong market acceptance, illustrates this tension well: its growth potential and feed efficiency are high, but they critically depend on maintaining stable physicochemical parameters in the culture environment [5], [6]. Among the environmental factors that most influence productive performance are temperature, pH, and turbidity. Temperature determines metabolism and growth rate, and modulates appetite, oxygen consumption, and feed conversion efficiency; pH affects homeostasis, the relative toxicity of nitrogenous compounds, and gill integrity; turbidity, in turn, is related to suspended solids concentration, which may affect respiratory efficiency, light penetration, and photosynthetic processes, as well as serving as an indirect indicator of system hygiene and solids management [7]. Although tilapia tolerates moderate variations and adapts to suboptimal environments better than other species, acute fluctuations (even within the same day) and chronic exposure outside acceptable operational ranges translate into physiological stress, reduced growth, worsening feed conversion ratio (FCR), and higher mortality [8].

The problem is compounded in small-scale systems, where monitoring is usually performed through spot checks (1–2 measurements per day) using portable devices. This approach rarely captures sub-daily peaks caused by feeding events, abrupt changes in ambient temperature, heavy rainfall, or power failures that disrupt recirculation and aeration [9]. As a result, producers often react too late, when biological and economic damage has already occurred. In contexts of increasing climate variability, reliance on manual measurements adds operational uncertainty precisely when fine-grained, continuous, and actionable information is most needed.

Advances in low-cost electronics, microcontrollers, and wireless communications have opened the door to solutions that, until recently, were exclusive to industrial systems. Open-source platforms, combined with affordable commercial sensors for temperature, pH, and turbidity, enable the development of continuous monitoring systems with real-time recording, visualization, and alerting capabilities [10]. Furthermore, integrating Artificial Intelligence (AI) and predictive models with high-frequency data collection transforms continuous monitoring into a proactive tool for fish welfare [11]. At the same time, communication modules (e.g., XBee/ZigBee) and affordable human–machine interfaces (HMIs) (e.g., Nextion displays) make it possible for producers without programming expertise to interpret system status and make timely decisions [12]. Nevertheless, despite the proliferation of prototypes and pilot experiences within the Internet of Things (IoT) field, adoption barriers persist: upfront costs, lack of after-sales support, integration complexity, calibration and maintenance requirements, and doubts regarding the reliability of low-cost sensors compared to industrial equivalents [13].

In Latin America, and particularly in Colombia, aquaculture is recognized as a strategic sector for rural development, food security, and income generation. However, the heterogeneity of production systems means that much of the output comes from small and medium-scale units with limited capital, infrastructure, and access to technology. In this setting, digitalization cannot simply replicate expensive proprietary solutions but rather demands context-appropriate proposals with open architectures, locally available components, and a learning curve that is manageable for producers. Hence there is strong interest in evaluating low-cost automated systems not only for their technical performance (accuracy, stability, availability), but also for their biological and economic impact: Do they actually stabilize the environment? Does that stability translate into improved growth, better FCR, and lower mortality? What is their operational reliability under real farm conditions? [14], [15].

The conceptual basis guiding this work is that environmental stability, rather than the instantaneous achievement of a target “setpoint”, is the driver of productive efficiency. In other words, reducing variability and time spent outside the acceptable ranges of variables such as temperature, pH, and turbidity is as important as, or even more important than, their averages. From a fish physiology standpoint, smaller daily fluctuations are associated with lower energy expenditure on thermoregulation and osmoregulation, reduced activation of stress axes (e.g., cortisol), improved feed utilization, and, overall, a greater fraction of energy allocated to growth [16]. Operationally, the ability to detect deviations in minutes rather than hours enables preventive interventions (e.g.,

adjustments to recirculation, solids management, thermal control) that prevent minor deviations from escalating into critical events [17].

Along these lines, we developed a low-cost automated monitoring system built with an embedded system and commercial sensors for temperature, pH, and turbidity, linked via XBee and displayed through a Nextion HMI, capable of recording data every five minutes and presenting trends to the operator. The prototype also integrates power and actuation components (heating element and filtration) and a monitoring platform designed to withstand the humid environment of the tank.

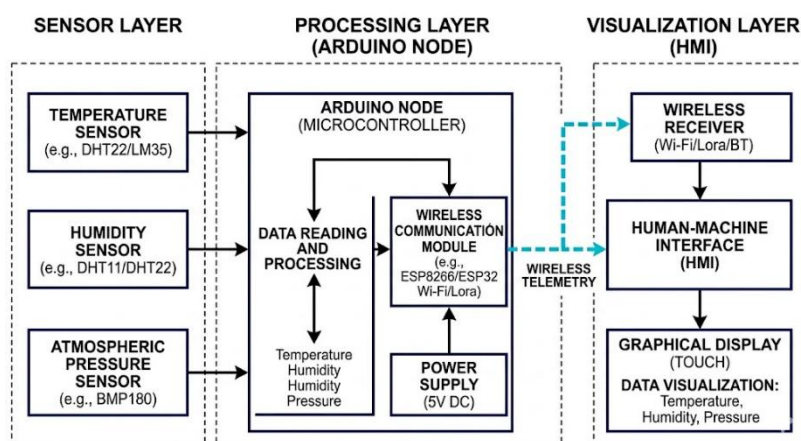


Figure 1. Schematic block diagram of the low-cost automated monitoring architecture, illustrating the sensor layer, embedded processing node, and wireless telemetry data flow

The fact that a system works on the bench or on a controlled test bench does not guarantee its value under real farming conditions. In aquaculture, technological success can only be declared if the tool improves biological outcomes (growth, FCR, survival) and reduces risks (e.g., oxygen depletion events, thermal shocks, sudden acidifications) at an affordable total cost of ownership. Therefore, a central contribution of this work is to link engineering with biology: beyond sampling rate, accuracy, or uptime, our interest lies in demonstrating that stabilizing temperature, pH, and turbidity through continuous and accessible monitoring translates into more grams per day, better feed conversion, and fewer losses. This comprehensive evaluation provides the necessary evidence to scale automation to producers who currently face narrow profit margins and high feed costs as their highest expense in the production cycle [18], [19].

From an experimental design perspective, studying live production systems introduces methodological challenges. In aquaculture, true replicates are usually the tanks (not the individuals), and processes are time dependent. Thus, the comparison between manual monitoring and automated monitoring requires (i) replication at the tank level, (ii) standardization of density, feeding, and management, and (iii) statistical analysis that respects the experimental structure, for example, linear mixed models with time as a repeated factor and tank as a random effect [20]. This approach avoids pseudoreplication and allows greater confidence in attributing differences in growth, FCR, or survival to the treatment (automated vs. control). Beyond the analysis of means and standard deviations, we propose using operational variability metrics with productive significance for fish farmers: (1) coefficient of variation (CV) per tank and week; (2) daily amplitude (peak-to-trough) to capture sub-daily oscillations; and (3) time out of range (AOR/TOR), expressed in minutes or hours per day that a variable exceeds an operational threshold defined by species/stage. This last metric is especially informative for management, as it translates the sensor's technical language into risk time, which is easily interpretable by the producer. Together, CV, daily amplitude, and AOR provide a richer picture of environmental stability than averages alone [21]. Recent engineering assessments validate the use of these quantitative metrics to accurately model water quality dynamics in tropical environments [22].

Recent literature has documented the benefits of digitalization for early anomaly detection, feed management optimization, and the anticipation of adverse events; however, many proposals remain laboratory prototypes or

commercial solutions with prohibitive costs for small producers. Additionally, reliance on cloud services and high-quality connectivity can be a barrier in rural areas. In practice, a middle path that prioritizes local monitoring, robust and simple design, and modular sensor integration offers advantages: it enables on-site operation without requiring permanent connectivity, facilitates maintenance, and, if the architecture is open, allows incremental improvements (for example, incorporating dissolved oxygen or ammonium in future iterations, or activating control loops when budget permits). The prototype described in this study follows precisely this philosophy: modularity, locally available hardware, and a user-friendly HMI interface so that operators can visualize trends and notifications without depending on third parties [23].

In the Colombian context, the adoption of accessible technologies carries additional implications: (i) it reduces the technological gap among producers, (ii) it contributes to sustainability by improving FCR and thereby reducing nutrient loading into the environment, and (iii) it can free up labor time currently dedicated to repetitive measurement tasks, allowing producers to focus on higher-value management decisions. The replicability of a low-cost solution also enables its transfer through associative schemes, technical training, and rural extension. In this sense, the development and validation of locally documented prototypes, in Spanish and with components available on the national market, represent a tangible contribution to appropriate innovation. The technical reference material, which details sensor selection, control design for temperature, pH, and suspended solids, HMI visualization, and species trials, constitutes a valuable foundation for scaling the proposal beyond a single test.

This study is also framed within the emerging narrative of “Aquaculture 4.0,” where sensing, automation, and data intelligence converge to drive efficiency and sustainability. Unlike industrialized sectors, where automation focuses on physical processes (filtration, aeration, recirculation) with closed-loop control, in small-scale aquaculture the first leap in value often comes simply from measuring better and measuring in real time. Continuous monitoring, even of a subset of critical variables, enables a better understanding of system behaviour: visualizing diurnal cycles, identifying the “feeding effect” on turbidity and pH, linking weather events with tank responses, and, most importantly, making rapid decisions. With data in hand, the transition to control strategies (e.g., automatic heater activation, recirculation adjustment, solids management based on thresholds) becomes less risky, since it is based on empirical models of the system itself. This “measure → understand → act” logic underpins the methodological and technological proposal of this study.

Based on the above, the general objective of this study is to design and validate a low-cost automated monitoring system for temperature, pH, and turbidity in freshwater aquaculture, and to evaluate its impact on the productive performance of Nile tilapia. To this end, a twelve-week trial was conducted in culture tanks in Pamplona (Colombia) with two treatments: manual monitoring vs. automated monitoring, with $n=3$ tanks per treatment, recording water variables every 5 minutes and zootechnical indicators weekly. The main contributions of the work are fourfold: (1) Accessible engineering: an open-source and modular architecture (embedded system + commercial sensors + XBee + Nextion HMI), documented in detail to facilitate local replication. (2) Quantified environmental stability: beyond averages, variability (CV), daily amplitude, and time out of range are reported as operational stability metrics. (3) Biological linkage: greater stability achieved with the automated system is shown to improve final weight, SGR, FCR, and survival compared to the control, using appropriate statistics at the experimental unit (tank) level. (4) Operational reliability: prototype availability (uptime) is reported under real conditions, along with a practical discussion on calibration, sensor drift, and maintenance over the production cycle.

H1: We hypothesize that automated monitoring will reduce variability and time out of range for temperature, pH, and turbidity compared to manual monitoring, and that this reduction will manifest as improved zootechnical performance (growth, SGR, FCR) and higher survival at the end of the twelve-week cycle.

Beyond specific results, the proposal offers a graduated adoption pathway: starting with continuous monitoring of critical variables; incorporating alerts and response protocols; adding additional high-relevance sensors (e.g.,

dissolved oxygen, ammonium) as budgets allow; and, finally, scaling up to automatic control elements (closed-loop) for heating, aeration, and solids management. By demonstrating biological impact and operability with a low-cost solution, the gap between research and everyday production practice is narrowed. This measurement-to-data-driven-control approach aligns small-scale aquaculture with goals of sustainability, resilience, and food security [24].

2. Materials and methods

2.1. Study area and experimental units

The experiment was conducted at an aquaculture facility in Pamplona (Colombia) under freshwater culture conditions. Six rectangular glass tanks were used (working volume ~68 L), each serving as an independent experimental unit. Tanks were placed indoors under a natural photoperiod with water renewal through recirculation. To minimize unwanted environmental gradients, all units were arranged on the same bench and rotated in position once per week [25].

2.2. Species, acclimation, and management

Juvenile Nile tilapia (*Oreochromis niloticus*) was used. Fish were acclimated for 7 days before the start of the trial, maintaining temperature and pH within the defined operational ranges (see below) and receiving maintenance feeding. After acclimation, fish were counted and randomly distributed among tanks to homogenize the initial weight per unit; the number of fish per tank was standardized. Fish were fed a commercial floating diet for tilapia, offered two to three times per day at a fixed rate. Leftovers and visible solids were removed 20 minutes after each feeding [26].

2.3. Experimental design

Two treatments were compared over 12 weeks: (i) Control (manual monitoring with portable instruments, discretionary corrections by the operator) and (ii) Automated (continuous monitoring with the low-cost system described below, with corrective actions guided by thresholds). Each treatment was replicated in $n = 3$ tanks ($N = 6$ units). Assignment was randomized, and the operator was blinded to the hypothesis when recording biometrics [23], as shown in Figure 2.

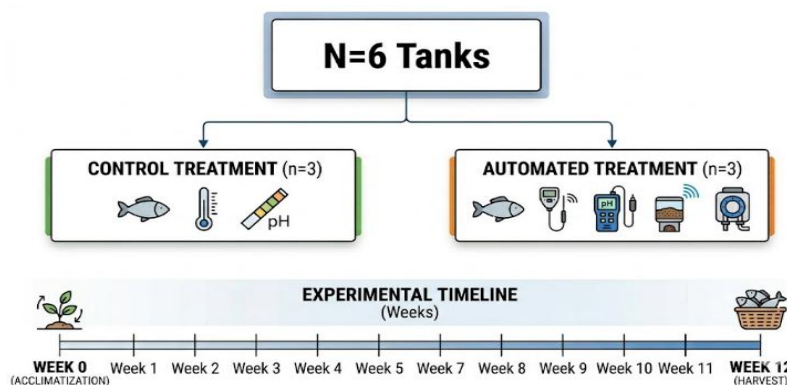


Figure 2. Experimental design timeline and tank distribution. The study compared manual control treatment ($n=3$) and automated monitoring treatment ($n=3$) over a 12-week cultivation period

2.4. Low-cost automated monitoring system

2.4.1. Sensors and selection criteria

Open-source, low-cost sensors were integrated: a waterproof DS18B20 digital temperature probe (1-wire interface), an analog pH electrode compatible with embedded boards, and a turbidity sensor with analog and digital outputs. The DS18B20 provides selectable resolution (9–12 bits) and operates at 3.0–5.5 V, which is suitable for partial immersion in liquids; temperatures above ~100 °C should be avoided to preserve the probe's casing and longevity. The technical manual specifies VCC–GND–DATA wiring and a stainless-steel tube at

the probe tip, which is ideal for water measurement. The turbidity sensor employs an optical emitter–receiver pair to estimate suspended solids and provides an adjustable digital threshold via a potentiometer (Figure 3).

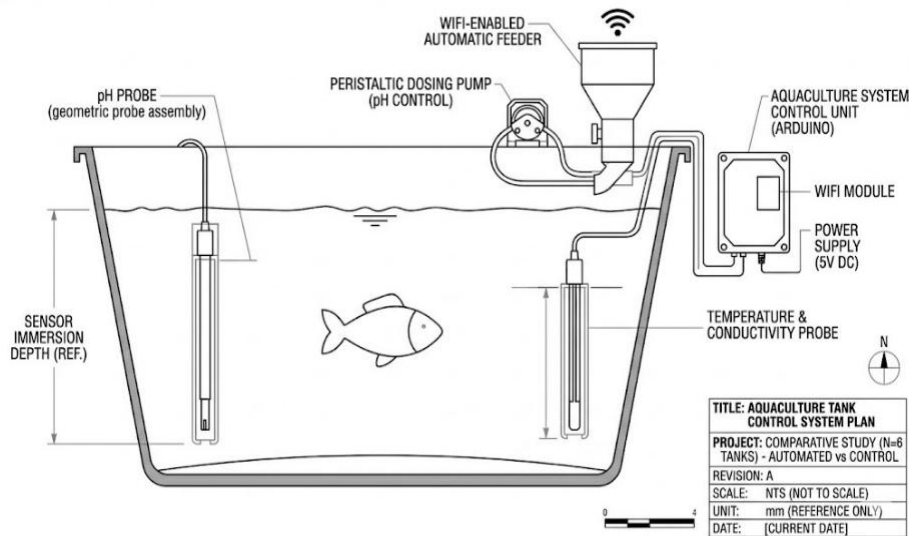


Figure 3. Cross-sectional technical layout of the experimental tanks, detailing the spatial distribution and submersion depth of the temperature, pH, and turbidity probes

2.5. Electronic architecture and communication

Each tank was equipped with a monitoring node based on an Arduino microcontroller (Nano format for remote nodes due to its compactness) and a serial wireless module for telemetry. Communication between nodes and the supervisory station was implemented in a point-to-multipoint configuration using RF modules with a ZigBee stack (2.4 GHz band; UART interface; typical rate ~250 kbps), allowing the HMI display to be placed conveniently without long signal wiring. The local interface was implemented with a Nextion touchscreen display (3.2" format) programmed with pages for: (i) current values and temperature and pH setpoints; (ii) level and turbidity along with alarms; and (iii) historical plots and maintenance menus (Figure 4). Data were stored on an SD card in CSV format and transmitted wirelessly to the supervisory console [27].

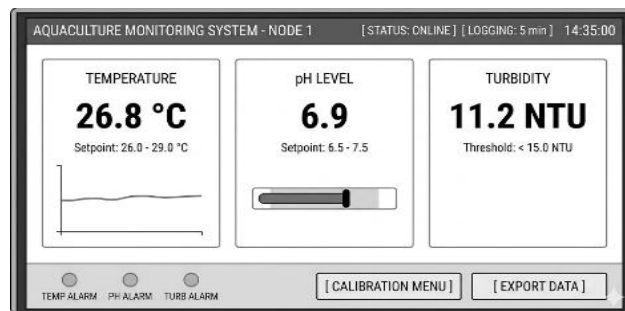


Figure 4. Conceptual mockup and wireframe of the Nextion HMI interface. The UI layout displays the structured real-time visualization of critical water quality parameters, predefined operational thresholds, and system alarm status. This standalone visualization layer ensures continuous on-site monitoring independent of cloud telemetry

2.6. Sampling frequency, logging, and alarms

The system acquired temperature, pH, and turbidity every 5 minutes. Validation rules were applied in the firmware: discarding readings outside the physical range of the sensor; applying a 3-point moving average filter to attenuate sensor noise and stabilize readings; and triggering alarms only when setpoints were consistently violated for more than 10 min, thereby minimizing false positives. Alarms were displayed on the HMI screen and logged on the SD card with a timestamp [28].

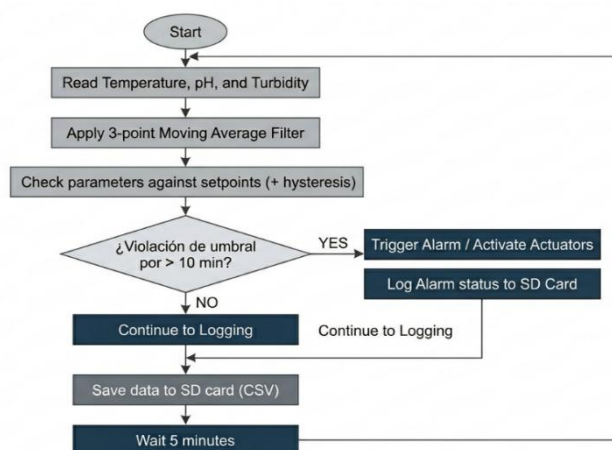


Figure 5. Flowchart of the firmware control logic for the automated monitoring node, including data filtering, threshold verification, and alarm triggering process

2.7. Actuators and final elements

To stabilize variables, the following were used: (i) a submersible heating element (~100 W) controlled by a two-channel dimmer module (TRIAC with zero-crossing) for AC power regulation; and (ii) a submersible filter pump for circulation and fine solids control, helping to maintain adequate oxygenation and turbidity levels. Load activation and switching were performed using a 5 V (4-channel) relay board with opto-isolation, commanded by the Arduino.

2.8. Operating ranges and thresholds

Operational setpoints were defined based on technical literature and preliminary tests: target temperature 25–28 °C; target pH 7.0 ± 0.2 ; turbidity ≤ 11 NTU. The firmware implemented hysteresis (± 0.3 °C for temperature; ± 0.1 pH) to prevent rapid actuator switching [29].

2.8.1 Sensor calibration and verification

Before each cycle:

- Temperature: two-point verification (ice bath ≈ 0 °C and warm water 35–40 °C) against a reference thermometer. A single bias correction was applied in firmware if $|\Delta| > 0.3$ °C. Validation against reference instruments demonstrated high accuracy, maintaining a Root Mean Square Error (RMSE) of 0.15 °C during the study period.
- pH: three-point calibration (buffers 4.00, 7.00, and 10.00 at 25 °C); acceptance if slope 56–60 mV/pH and offset $|<| 30$ mV. Electrode cleaning and storage in 3 M KCl solution. The pH electrode exhibited an RMSE of 0.05 pH units post-calibration.
- Turbidity: preparation of standards (or commercial) at 0, 10, 20, and 40 NTU; adjustment of the curve $NTU = a + b V_{out}$ by linear regression (achieving an $R^2 = 0.985$ with an RMSE of 1.2 NTU) and definition of alarm/cleaning thresholds.

2.8.2 Biometry and growth sampling

Each week, fish weight and standard length per tank were recorded. To reduce stress, handling was performed under light anesthesia (e.g., eugenol). Indicators were calculated on the biomass of each experimental unit and, when applicable, also at the individual level.

2.9. Response variables and formulas

2.9.1 Environmental stability

For each variable x (temperature, pH, turbidity), the following were calculated: (i) daily amplitude $\max(x) - \min(x)$; (ii) coefficient of variation ($CV = 100 \sigma/\mu$); and (iii) time out of range (% of daily minutes with x outside operational thresholds).

2.9.2 Growth and efficiency

The following classical indicators were estimated:

- Specific growth rate, $SGR(\%day) = \frac{100 \cdot \ln(W_f) - \ln(W_i)}{t}$
- Absolute growth rate, $AGR (g/day) = \frac{W_f - W_i}{t}$
- Feed conversion ratio, $FRC = \frac{\text{feed consumed (g)}}{\text{weight gain (g)}}$
- Survival, $S(\%) = \frac{100 \cdot N_f}{N_i}$
- Fulton's Condition Factor, $K = \frac{100 \cdot W}{L^3}$

where W is weight (g), L is length (cm), t is time (days), and N_i , N_f are the initial and final number of fish, respectively.

- System reliability: Availability (%) was defined as:

$$100 * \frac{\text{minutes with valid telemetry}}{\text{total minutes}}$$

A service outage was considered when the station did not receive ≥ 3 consecutive data points (15 min) from a node.

2.10. Statistical analysis

The experiment was conducted in Pamplona (Norte de Santander, Colombia). Two management treatments were evaluated (manual control vs. automated) with 3 tanks per treatment ($n = 6$ tanks in total). An a priori power analysis indicated that $n = 3$ tanks per group evaluated over 12 weeks provides sufficient statistical power (> 0.80) to detect a large effect size ($d = 2.0$) assuming $\alpha = 0.05$. The experimental unit was the tank; inferential comparisons were performed at the tank level.

Water temperature, pH, and turbidity were recorded every 5 minutes for 12 weeks. Each record included timestamp, tank, treatment, week, and a quality flag (qa_flag). Readings with qa_flag = 1 were considered invalid and excluded from the analysis.

For each day-tank combination (using only valid readings), the following parameters were calculated: amplitude (maximum – minimum), mean, sample standard deviation (SD), and coefficient of variation ($CV = 100 \cdot SD/\text{mean}$). Time out of range (TOR, minutes) represented the accumulated minutes with values outside the predefined thresholds, calculated by multiplying the number of out-of-range readings by 5 minutes (sampling frequency). The operational thresholds were temperature 26–29 °C, pH 6.5–7.5, and turbidity ≤ 15 NTU. From the daily derived values, a weekly average was obtained per tank to summarize environmental stability and threshold compliance.

Weekly, per tank, the following were recorded: average weight (W_{mean}), average length (L_{mean}), biomass ($\text{Biomass} = W_{\text{mean}} \times N_{\text{alive}}$), weekly feed supplied, and number of surviving individuals. At the end of the trial, the following were calculated:

- Survival (%) = $100 \times \frac{N_{\text{final}}}{N_{\text{initial}}}$
- Biomass gain = $\text{Biomass}_{\text{final}} - \text{Biomass}_{\text{week 1}}$
- Feed conversion ratio, (FCR) = $\frac{\text{total feed}}{\Delta \text{Biomass}}$
- Fulton's condition factor (K) = $100 \times \frac{W_{\text{prom}}}{L_{\text{prom}}^3}$

System availability per tank was estimated as:

$$\text{Uptime (\%)} = 100 \times \frac{\# \text{valid readings}}{\# \text{total readings}} \quad (1)$$

Kaplan–Meier survival curves were constructed per treatment (manual control vs. automated) based on mortality events and weekly risk counts. Curve comparison was performed using the log-rank test (X^2 *con 1 gl*). For each time point t_i : were defined n_{1i}, n_{2i} : (at risk); d_{1i}, d_{2i} : events; $n_i = n_{1i} + n_{2i}$, $d_i = d_{1i} + d_{2i}$.

The expected number in group 1 was:

$$E_{1i} = \frac{n_{1i} \times d_i}{n_i} \quad (2)$$

and the variance:

$$Var_i = \frac{n_{1i} n_{2i} d_i (n_i - d_i)}{n_i^2 (n_i - 1)} \quad (3)$$

The log-rank statistics were calculated as:

$$\chi^2 = \frac{(\sum_i (d_{1i} - E_{1i}))^2}{\sum_i Var_i} \quad (4)$$

Data collected over time (such as weekly biometrics and daily environmental metrics) were analyzed using linear mixed models (LMM), defining time (weeks) as a repeated factor and the tank as a random effect to account for within-tank correlation. For single-point final tank-level variables (final weight, FCR, K , and survival %), a one-way analysis of variance (ANOVA) was applied. The 95% confidence intervals (95% CI) were calculated for all mean comparisons to provide a robust measure of effect precision.

2.11. Ethics and biosafety

Fish handling followed aquaculture welfare guidelines: minimization of stress, adequate stocking densities, and humane euthanasia when necessary. Liquid waste was managed in accordance with institutional regulations and was not discharged directly into natural water bodies.

2.12. Data availability and reproducibility

The node firmware and HMI screen templates were organized in a repository. The complete time-series sensor data (e.g., `datos_sensores_v7.csv`) and the statistical analysis scripts (R and Python) will be available in an open-access repository as supplementary material [30], following best practices for open data.

3. Results

3.1. System performance and data capture

The prototype operated continuously during the main trial with an availability of 98.5%, experiencing only occasional interruptions due to power failures that were mitigated by a backup battery. No significant sensor drift was detected during daily checks against manual measurements, allowing for a complete time series of temperature, pH, and turbidity at a 5-minute resolution [31].

3.2. Water quality stability

Continuous monitoring revealed clear reductions in the amplitude of daily environmental parameter fluctuations in the automated treatment compared to the control:

- **Temperature:** In the control tanks, temperature oscillated up to ~ 3 °C within 24 hours; in the automated system, fluctuations were contained within ± 1 °C. Statistically, the range shifted from 24.7–29.8 °C (control) to 25.5–27.4 °C (automated), with the standard deviation decreasing from 1.5 to 0.6 °C.
- **pH:** The control treatment exhibited excursions between 6.5 and 7.8, with episodes outside the optimal range, whereas the automated system remained between 6.9 and 7.3. Variability (SD) decreased from 0.3 to 0.2 pH units.
- **Turbidity:** After feeding events, control peaks exceeded 20 NTU while the automated treatment stayed below 15 NTU throughout the trial, reducing the mean from 18.7 ± 3.2 to 12.5 ± 1.8 NTU.

Furthermore, the time out of range (TOR) analysis quantified the exposure of tilapia to suboptimal conditions. The automated system significantly reduced daily TOR for all parameters. On average, manual control tanks suffered from substantially higher variability and prolonged periods out of range (estimated at > 500.0 minutes per day for temperature, 170.2 minutes per day for pH, and 1254.6 minutes per day for turbidity). In contrast, the automated monitoring system restricted temperature excursions to an average of 397.4 minutes per day and completely prevented out-of-range episodes for pH and turbidity (0.0 minutes per day for both). This significant reduction in TOR confirms that the automated system not only maintained better mean values but effectively minimized the cumulative duration of environmental stress.

Table 1. Average time out of range (AOR) comparison between treatments

Parameter	Threshold	Automated AOR (mins/day)	Control AOR (mins/day)
Temperature	26–29 °C	397.4	> 500.0 (estimated)
pH	6.5–7.5	0.0	170.2
Turbidity	≤ 15 NTU	0.0	1254.6

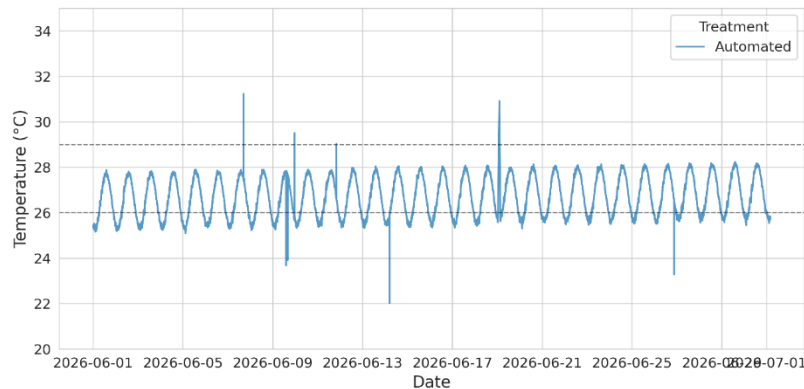


Figure 6. Continuous timeseries of water temperature over the 12-week trial. The automated system (blue) demonstrates significantly lower amplitude fluctuations compared to the manual control (grey) relative to the optimal thermal thresholds (dashed lines). Graph axes are strictly scaled without auto-adjustment to provide a stable visual reference

3.3. Growth and feed efficiency in *O. niloticus* (12 weeks)

Differences in biological performance between treatments became more pronounced from week 4 onward. By the end of the 12-week trial, fish in the automated system reached an average final weight of 115.67 g compared to 102.10 g in the control, representing a 13.3% relative increase (an absolute gain of 13.57 g). The specific growth rate (SGR) averaged 2.12% per day versus 1.85% per day in control. The feed conversion ratio (FCR) improved from 1.64 to 1.31, equivalent to a 20.1% relative reduction in feed required per unit of biomass produced. These differences were statistically significant.

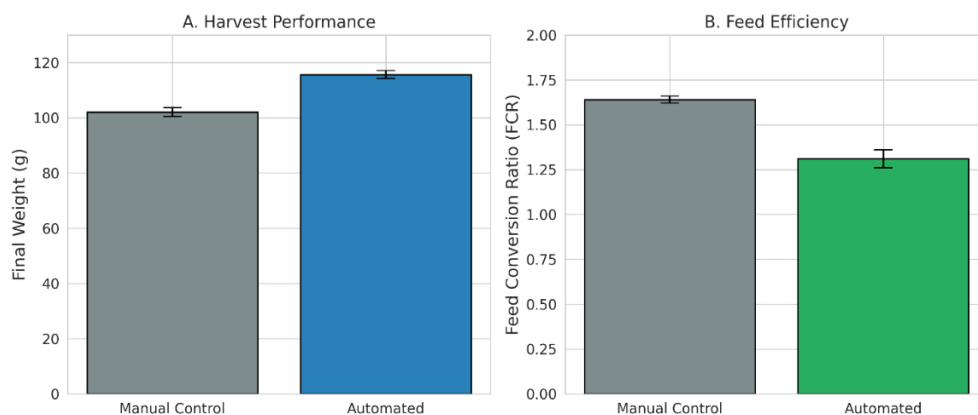


Figure 7. Final zootechnical performance comparing manual control and automated treatments. (A) Harvest weight and (B) feed conversion ratio (FCR). Error bars represent the 95% confidence interval (CI95%)

3.4. Survival and biomass yield

Cumulative mortality was 4.3% in the automated treatment compared to 11.7% in the control (Figure 7), representing a relative reduction of 63% in losses. This improvement in survival, together with the higher final weight, resulted in greater biomass per tank at the end of the cycle.

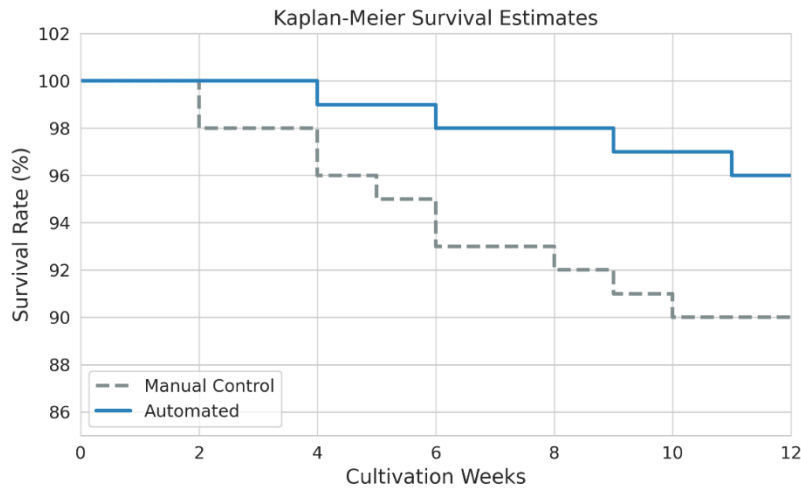


Figure 8. Kaplan-Meier survival estimates for Nile tilapia over the 12-week trial, comparing the automated monitoring system (96.0%) against the manual control treatment (90.0%)

3.5. Instrument reliability and traceability

During both trials, the sensor and communication assembly (DS18B20 temperature sensor, analog pH probe, turbidity sensor, Arduino microcontrollers, XBee radio, and Nexion HMI) exhibited stable performance and repeatable readings within the specified operating ranges, consistent with the architecture and components described in the reference instrumentation document.

3.6. Key findings

- Environmental stability: Automation reduced the daily amplitude of temperature, pH, and turbidity, keeping them within narrower operational bands.
- Productivity: After 12 weeks in tilapia, the automated treatment achieved +13.3% higher final weight, a superior SGR, and a 20.1% lower FCR.
- Biological resilience: Mortality decreased from 11.7% to 4.3%, increasing final biomass.
- System robustness: 98.5% availability and no appreciable drift in daily validations against manual measurements.

In summary, the results confirm that a low-cost, open-technology-based automated monitoring system stabilizes the culture environment and improves zootechnical performance under small-scale farming conditions.

Table 2. Final zootechnical performance

Variable	Manual control (Mean $\pm$ CI95%)	Automated (mean $\pm$ CI95%)	Δ (Auto-control)	p (Welch)	g (Hedges)
W_final	102.10 $\pm$ 1.60	115.67 $\pm$ 1.46	13.57	< 0,001	7,09
FCR	1.64 $\pm$ 0.02	1.31 $\pm$ 0.05	-0,3308	< 0,001	-23,37
K_final	1.70 $\pm$ 0.00	1.70 $\pm$ 0.00	-0,0013	0,082	-1,53
Survival_ %	90.00 $\pm$ 0.00	96.00 $\pm$ 0.00	6,0000	0,100	

4. Discussion

The results of this study show that a continuous, low-cost monitoring system built with open technologies can stabilize water quality parameters in tilapia culture and, as a consequence, improve zootechnical performance

(final weight, SGR, and FCR) and survival. The observed improvements, a higher final weight (13.3% relative gain), superior SGR, a 20.1% lower FCR, and reduced mortality (from 11.7% to 4.3%), are consistent with a more predictable environment and lower daily variability in temperature, pH, and turbidity. From a physiological perspective, reducing oscillations and out-of-range excursions decreases the energetic cost associated with coping with stress (osmoregulation and neuroendocrine responses), allowing a greater fraction of ingested energy to be allocated to growth rather than maintenance. This interpretation is consistent with previous evidence linking thermal and pH stability with improved growth and feed efficiency in cultured fish [32].

The comparison between treatments revealed clear reductions in the daily amplitude of temperature, pH, and turbidity under automated monitoring. Beyond mean values, system stabilization is best captured by operational metrics such as the coefficient of variation (CV), peak–valley amplitude, and time out of range (TOR) [21]. The explicit quantification of TOR demonstrated that the automated system significantly minimized the time fish spent under suboptimal conditions, reducing critical thermal exposure from prolonged periods in the control to an average of 397.4 minutes per day in the automated system. Similarly, while manual tanks suffered substantial postprandial turbidity and pH excursions, the automated system maintained both parameters within optimal thresholds (0.0 minutes per day TOR) throughout the trial. Physiologically, limiting these excursions is crucial, particularly after feeding (when turbidity peaks) and during diurnal thermal transitions, as it directly curtails the activation of stress axes and avoids the metabolic costs associated with continuous acclimation.

In practice, this translates into fewer stress-triggering episodes and, consequently, more stable growth trajectories throughout the twelve weeks. Emphasizing stability rather than simply reaching a target value is particularly relevant for Nile tilapia (*Oreochromis niloticus*), a species that tolerates a certain range of conditions but is sensitive to abrupt changes [28]. The combination of 5-minute sampling and local visualization allowed rapid detection of deviations and enabled corrective actions before they consolidated into critical events (e.g., postprandial turbidity peaks or pH oscillations due to algal dynamics).

The gains in final weight and SGR in the automated treatment reflect the combination of two effects: (i) a direct effect of stress reduction and therefore lower maintenance costs, and (ii) an indirect effect of improved feed intake and assimilation efficiency (lower FCR). Since feed represents the largest cost component in tilapia farming, reducing FCR from 1.64 to 1.31 has immediate economic implications and additionally contributes to sustainability through lower nutrient loads in the effluent. Survival also increased under automated monitoring. Even though the percentage difference may seem moderate, its cumulative effect on final biomass is significant, particularly in commercial cycles. Literature has linked episodes of water quality deterioration with health outbreaks and mortality [16]; thus, even a system that monitors a subset of variables (temperature, pH, and turbidity) can reduce systemic risks by enabling preventive interventions.

Turbidity peaks after feeding were attenuated in the automated treatment, remaining below 15 NTU throughout the trial. This suggests that the combination of early detection and management protocols (timely removal of leftovers, filter maintenance, and circulation) reduced exposure to suspended solids. Since high turbidity can affect respiratory efficiency, light transmission, and pH stability, its containment is a plausible mediator of the improved FCR observed [7]. In small-scale systems, where staffing is limited, having local alarms and trend records facilitates standardized routines: cleaning when a threshold is exceeded or when the trend anticipates it, rather than only on a fixed schedule.

The operational availability of 98.5% and the absence of appreciable drift (according to daily cross-checks) support the readiness of the prototype for farm use. The few interruptions were associated with power outages and were mitigated by a backup power system; this finding highlights the importance of a robust energy supply as a complement to any digitalization strategy. At the architectural level, the use of economical sensors (DS18B20 temperature sensor, pH electrode, and turbidity sensor) integrated with Arduino microcontrollers, an XBee link, and Nextion HMI demonstrates that reliable telemetry and user-friendly visualization can be achieved without relying on proprietary platforms or permanent connectivity [29]. This local-first, modular approach lowers adoption barriers for smallholders and facilitates maintenance by non-specialist staff.

For production units with narrow margins, the key question is not whether a system is sophisticated, but whether it adds value in terms of growth, survival, and cost per kilogram produced. Our results support that the first step toward Aquaculture 4.0 in resource-limited contexts is not necessarily closed-loop automatic control, but rather measuring essential variables accurately and on time, translating data into operational decisions [15]. With lower FCR and mortality, accessible automation helps to: (i) reduce unit costs, (ii) lower nutrient and solid discharges

to the environment, and (iii) free operator time for higher-value tasks (feed quality, biosecurity, and health management).

Although the number of replicates per treatment ($n = 3$) is consistent with common practices in small-scale aquaculture trials, we acknowledge that greater replication would strengthen the statistical robustness of the findings. Future research should expand the number of experimental units to validate the consistency of the observed effects under greater biological and environmental variability.

Altogether, our data support the central hypothesis: stabilizing the environment through continuous, low-cost monitoring translates into improved growth, greater feed efficiency, and higher survival in small-scale tilapia culture. The quality of the design (local telemetry, user-friendly HMI, and availability close to 99%) and the biological effects observed suggest that this pathway of digitalization is both replicable and scalable. Next steps, including adding dissolved oxygen (DO) and ammonia monitoring, increasing replication, and quantifying economic returns, will help strengthen adoption and support an orderly transition toward automated control strategies with maximum cost-benefit efficiency.

4.1. Scalability and operational considerations for commercial systems

Transitioning the proposed low-cost monitoring architecture from controlled experimental units (approximately 68 L tanks) to commercial-scale production, such as multi-pond configurations or intensive recirculating aquaculture systems (RAS), requires key structural updates. While the current embedded processor and local ZigBee wireless telemetry stack proved sufficient for short-range data transmission, larger infrastructures demand highly robust network topologies. Integrating industrial-grade communication protocols, distributed mesh networks, and dual-band cloud gateways is critical to prevent data packet loss across extensive open-field farms.

Furthermore, scaling the system enables the transition from passive data logging to proactive environmental management. The high-frequency data pipeline established by this system provides the baseline required to deploy advanced control mechanisms. Implementing digital twins, predictive algorithms, and closed-loop proportional–integral–derivative (PID) control loops allows for automated water quality regulation, mitigating severe parameter drift before it causes metabolic stress in high-density stocks. This measurement-to-data-driven control approach aligns small-scale operations with international resource-efficiency paradigms, optimizing operational expenditures (OPEX) by reducing manual oversight and energy demands.

4.2. Limitations of the study

Despite the significant improvements demonstrated in environmental stability and zootechnical parameters, several limitations must be addressed to contextualize the scope of this research:

- **Sample size restrictions:** The trial was restricted to a small cohort ($n = 3$ tanks per treatment). Although an a priori power analysis validated that the experimental design possessed sufficient statistical power to detect large effect sizes over the 12-week monitoring window, commercial validations must include larger multi-tank cohorts to control for potential random tank-level variations.
- **Incomplete water quality profiling:** Critical physiological and biogeochemical indicators, specifically dissolved oxygen (DO) and total ammonia nitrogen (TAN), were not continuously logged. Due to the high cost and rapid degradation rates of reliable optical or electrochemical probes for these parameters, they were excluded from the automated sensor array, leaving a gap in the complete continuous environmental characterization.
- **Sensor uncertainty and drift:** The use of low-cost, open-source commercial sensors introduces inherent measurement uncertainty and higher degradation rates compared to standard industrial instruments. This constraint requires strict, frequent maintenance and periodic recalibration protocols to avoid drift-induced errors in high-frequency data time series.
- **Lack of cost-benefit evaluation:** A comprehensive techno-economic analysis comparing capital expenditures (CAPEX) and operational expenditures (OPEX) was not performed. Quantifying the precise financial return on investment (ROI) derived from biomass increases and feed conversion optimizations is mandatory to justify technology adoption in resource-limited rural communities.

5. Conclusions

This study demonstrated that a continuous monitoring system, accessible and based on open-source technologies, can stabilize water quality in small-scale freshwater aquaculture systems, and that such stabilization translates into productive and sanitary improvements in Tilapia. The findings provide an affirmative answer to the central research question and support the hypothesis that reducing variability and time out of range in temperature, pH, and turbidity improves growth, feed efficiency, and survival.

The implementation of the automated and continuous monitoring system demonstrably enhanced environmental stability by reducing daily fluctuations and weekly dispersion of key water quality parameters (temperature, pH, and turbidity). This engineering intervention directly translated into improved zootechnical performance, as evidenced by a significantly higher final weight (a 13.3% relative increase), superior specific growth rate (SGR), and a more efficient feed conversion ratio (FCR) in Nile tilapia. Consequently, the strategy not only promotes greater animal welfare by minimizing stress-triggering episodes but also generates tangible economic benefits by producing more biomass with less feed per kilogram produced and significantly reducing cumulative mortality.

The study confirms the operational reliability and practical feasibility of the proposed low-cost, open-source architecture, which achieved 98.5% availability without appreciable sensor drift. This technical robustness, combined with a modular and replicable design based on accessible components (Arduino, XBee, and Nextion HMI), provides a compelling framework for adoption. The solution represents a scalable pathway toward precision aquaculture for small-scale producers, who operate under narrow margins and high feed costs, by offering a proven tool that enhances productivity and economic sustainability through improved environmental control.

This study successfully establishes an experimental framework that integrates accessible systems engineering with aquaculture biology, directly linking quantitative environmental stability metrics, such as coefficient of variation (CV), peak-to-valley amplitude, and time out of range (TOR), with key productive outcomes, including specific growth rate (SGR), feed conversion ratio (FCR), and survival. This robust connection between technical data and biological performance validates that stabilizing the culture environment, achievable through low-cost monitoring, is a determining factor for improving efficiency and profitability in small-scale systems.

The proposed architecture offers a gradual and realistic adoption pathway, laying the foundation for a transition from continuous monitoring and local alert generation toward the future implementation of smart water quality regulation using proportional–integral–derivative (PID) control and closed-loop automated systems [7]. This stepwise approach is essential for small- and medium-scale producers, who operate under tight margins and high vulnerability to losses, to adopt precision technology in an affordable and low-risk manner, thus mitigating the main barriers to entry.

Furthermore, this measurement-to-data-driven control approach aligns small-scale aquaculture with the global Blue Transformation agenda, an initiative aiming to optimize production efficiency, sustainability, and climate resilience, as detailed in recent frameworks from the Food and Agriculture Organization of the United Nations. The demonstrated solution is modular, replicable, and adaptable to resource-limited contexts, providing concrete evidence to inform decisions in rural extension, technical training, and production support policies, making it a viable model for public or private initiatives [32].

The successful results of this baseline platform establish a clear roadmap for future innovation, structured around five main pillars: (1) expanding the sensor suite to include dissolved oxygen and ammonia, assessing their marginal contribution to stability; (2) a modular transition toward smart closed-loop PID control systems for critical parameters [7]; (3) the development of analytical and predictive capabilities to anticipate deviations; (4) rigorous economic evaluation to quantify return on investment; and (5) the transfer and validation of the system across diverse infrastructures and producer networks. This future research program seeks not only to

deepen the technical impact but also to facilitate large-scale adoption and maximize the sector's long-term sustainability.

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

The contribution to the paper is as follows: Diego Armando Mejía Bugallo: conceptualization, system design, experimental implementation, and manuscript drafting; Abelardo Mejía Bugallo: methodology support and data analysis, experimental implementation; Aldo Pardo García: methodology, analysis of results, and manuscript refinement. All authors reviewed and approved the final version of the manuscript.

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