Egyptian Journal of Aquatic Biology and Fisheries
Zoology Department, Faculty of Science,
Ain Shams University, Cairo, Egypt.
ISSN 1110 – 6131
Vol. 29(4): 1817 – 1830 (2025)
www.ejabf.journals.ekb.eg

IoT Systems Integration for Zootechnical and Aquatic Environment Optimization in Semi-Intensive Red Tilapia (*Oreochromis* spp.) Culture

Ruth María Farías Lema*, Ruth Rubí Peña Holguín, Sonnia Valeria Zapatier Castro
Centro de Estudios Estadísticos, Universidad Estatal de Milagro (UNEMI), 091050 Milagro, Ecuador

***Corresponding Author: rfariasl1@unemi.edu.ec**

ARTICLE INFO
Article History:
Received: May 14, 2025
Accepted: July 13, 2025
Online: July 27, 2025

Keywords:
Internet of Things,
Oreochromis spp.,
Water quality,
Intensive aquaculture,
Automated monitoring,
Zootechnical performance

ABSTRACT

Oreochromis spp., a widely cultured species in tropical aquaculture systems, requires stable environmental conditions and continuous monitoring to achieve optimal productivity. This study evaluated the impact of three levels of IoT-based technological implementation on production performance and water quality during a 60-day intensive culture period. Three treatments were established: T1 (manual monitoring), T2 (IoT sensors without automation), and T3 (automated IoT system with aeration control, water recirculation, and real-time alerts). Physicochemical parameters—including temperature, dissolved oxygen, pH, total ammonia, and turbidity—were monitored alongside zootechnical variables such as weight gain, specific growth rate (SGR), feed conversion ratio (FCR), and survival rate. The T3 treatment demonstrated superior water quality, with significantly lower levels of ammonia (0.19 ± 0.03 mg/L) and turbidity (9.1 ± 1.4 NTU), and higher concentrations of dissolved oxygen (5.60 ± 0.24 mg/L) compared to T1. Productive performance was also the highest in T3, with an average weight gain of 221.9 ± 11.7g, an SGR of 2.78 ± 0.10%/day, and a survival rate of 97.8 ± 1.5%. In terms of operational efficiency, the automated IoT system (T3) exhibited an average response time of 2.3 minutes to critical events and detected environmental alarms at a higher frequency (approximately 2.9 alerts/day), indicating improved sensitivity and responsiveness. These findings conclude that IoT-based automation significantly enhances operational efficiency, stabilizes aquatic ecosystems, and improves production performance in intensive *Oreochromis* farming systems. The integration of sensors, distributed logic, and real-time monitoring emerges as a strategic innovation for promoting a more resilient, sustainable, and technologically advanced aquaculture sector.

INTRODUCTION

Fish farming has emerged as one of the most efficient strategies to meet the growing global demand for high-quality animal protein **(FAO, 2022)**. Among farmed species, tilapia (*Oreochromis* spp.) stands out due to its rapid growth, adaptability to intensive production systems, and high feed conversion efficiency **(El-Sayed, 2006)**. Globally, aquaculture now supplies over 50% of fish intended for human consumption, with significant contributions from Africa, Asia, and Latin America **(Naylor *et al.*, 2021)**. In Ecuador, tilapia farming plays a vital role in rural food security, particularly in tropical coastal regions where year-round production is supported by favorable environmental conditions **(Zuñiga & Goycolea, 2014)**.

One of the main challenges in intensive aquaculture is the effective management of key water quality parameters—such as temperature, dissolved oxygen, pH, ammonia, and turbidity—that directly influence fish metabolism, survival, and feed efficiency **(Pulkkinen *et al.*, 2018; Nairuti *et al.*, 2021)**. Traditionally, water quality monitoring relies on manual methods and operator experience, which can limit the timely detection and correction of adverse conditions. In response, sensor-based Internet of Things (IoT) technologies offer new opportunities for real-time environmental monitoring, automated control, and predictive data analysis **(Chen *et al.*, 2022; Cardozo *et al.*, 2024)**.

The integration of digital tools in aquaculture facilitates the early detection of environmental risks, activation of control mechanisms (e.g., aerators or water pumps), and reduction of production losses related to stress-induced mortality **(Le *et al.*, 2024)**. A growing body of research supports the benefits of intelligent aquaculture systems, showing that IoT and automation can improve production efficiency, lower labor demands, and enhance fish welfare in recirculating aquaculture systems (RAS) **(Terjesen *et al.*, 2013; Shi *et al.*, 2018)**. Distributed control architectures using microcontrollers (e.g., ESP32), along with sensors for monitoring temperature, dissolved oxygen, and pH, enable high-frequency data acquisition and environmental control **(Piamba *et al.*, 2020)**. Additionally, platforms like Node-RED and ThingSpeak allow for autonomous system logic, remote monitoring, and data transmission via mobile networks or Wi-Fi **(Misra *et al.*, 2022)**.

These innovations contribute to the development of predictive and adaptive systems aligned with the principles of Aquaculture 4.0 and the goals of sustainable intensification.

The objective of this study was to evaluate the impact of varying levels of IoT-based technological implementation on water quality management and production performance of *Oreochromis* spp. in an intensive aquaculture system. Additionally, the operational behavior of the monitoring and automation platform was analyzed in terms of responsiveness and alert generation. The findings aim to support the optimization of aquaculture production systems through the integration of digital technologies and the adoption of smart aquaculture practices.

MATERIALS AND METHODS

Study area

The present study was conducted at Hacienda La Chorrera, located in the canton of Chone, province of Manabí, Ecuador (0°41′52″ S, 80°05′15″ W), a region characterized by a humid tropical climate, with average annual temperatures between 25 and 28°C, high relative humidity (above 75%) and an annual rainfall exceeding 1000mm, concentrated mainly during the first four months of the year. These environmental conditions favor the semi-intensive cultivation of *Oreochromis* spp. by providing a thermally stable environment with abundant freshwater availability.

Species selection

Oreochromis spp., an interspecific hybrid commonly used in tropical aquaculture, was selected for this study due to its rapid growth, high feed efficiency, and resilience to variable environmental conditions. Juveniles with an average initial weight of 10g were sourced from a certified hatchery and subjected to standard health screening protocols prior to stocking.

Sample collection

Sampling was conducted weekly over a 60-day period. For the evaluation of production parameters, three representative individuals per experimental unit were manually captured using fine mesh nets. Body weight and total length were measured using a precision digital scale (±0.01 g) and an ichthyometer, respectively.

Water quality parameters were recorded in situ using IoT-connected digital sensors and validated with standard analytical kits. Measured variables included temperature, pH, dissolved oxygen, total ammonia, and turbidity. All measurements were conducted at the same time each day to ensure data comparability and consistency across treatments.

Experimental design

The study followed a completely randomized design with three levels of technological treatment and three replicates per treatment, totaling nine experimental units. Each unit consisted of a 3m³ circular tank, uniformly configured for water flow, aeration, and feeding conditions. The stocking density was 100 fish/m³, using juveniles of *Oreochromis* spp. selected for their growth performance and environmental tolerance.

The experimental treatments varied by the degree of IoT technological implementation for environmental monitoring and control:

- **T1:** Traditional manual monitoring using handheld instruments and physical data recording.
- **T2:** IoT sensors enabling real-time data acquisition and visualization, without automated responses.
- **T3:** Fully automated IoT system integrating sensors with programmable logic controllers (Node-RED) to activate aerators, pumps, and warning systems based on pre-set thresholds.

This structure allowed for evaluation of the incremental benefits of automation, following RAS efficiency frameworks proposed by **Terjesen *et al.* (2013)**, which emphasize the importance of real-time control and data integration for animal welfare and environmental stability.

Parameters evaluated

Over the course of the study, variables were grouped into three categories for assessment:

1. **Productive performance**: Weight gain, specific growth rate (SGR), feed conversion ratio (FCR), and survival rate.
2. **Water quality**: Temperature, dissolved oxygen, pH, total ammonia, and turbidity.
3. **IoT system performance**: Responsiveness to critical events and alert generation frequency.

Water quality monitoring

Water quality was continuously monitored using distributed digital sensors connected via IoT infrastructure, focusing on parameters critical to the metabolism and health of *Oreochromis* spp.

- **Temperature (°C):** Recorded every 5 minutes using DS18B20 submersible sensors, due to its influence on metabolic rate, oxygen solubility, and ammonia toxicity.
- **Dissolved Oxygen (mg/L):** Measured with high-precision optical sensors (Atlas Scientific), essential for preventing hypoxic stress and supporting optimal growth, particularly under high stocking densities.
- **pH:** Monitored using calibrated electronic electrodes, considering its role in ammonia speciation and bioavailability.
- **Total Ammonia (mg/L):** Estimated daily via algorithmic correlation with temperature and pH and validated weekly using colorimetric kits. The non-ionized NH_3 fraction, being highly toxic, was given particular attention as a critical threshold in RAS operations.
- **Turbidity (NTU):** Measured every 15 minutes using TSD-10 sensors as a proxy for suspended solids, organic load, and biofilter efficiency.

The monitoring frequency and parameter selection were aligned with the best technical practices to ensure system stability, reduce health risks, and sustain biological treatment efficiency in recirculating aquaculture systems **(Terjesen *et al.*, 2013)**.

Productive performance

The productive variables were measured weekly by direct sampling of three individuals per experimental unit. Weight gain (g) was obtained as the difference between the initial weight and the weight recorded weekly, using a precision scale (±0.01 g). Specific growth rate (SGR, %/day) was calculated using the formula:

$$SGR = \frac{ln\,(w_f) - \ln(w_i)}{t} \times 100$$

Where, w_f is the final weight, w_i the initial weight, and t: the number of days of the period. This formula was proposed by **Ricker (1979)** and has been adopted in intensive systems studies by authors such as **Rodríguez *et al.* (2025)** because of its usefulness in analyzing relative growth independent of initial size.

Feed conversion ratio (FCR) was calculated as the ratio between the feed supplied (kg) and the weight gain obtained (kg), its inverse being feed efficiency (FE), a key parameter for the economic and environmental evaluation of the system. Finally, survival (%) was estimated at the end of the period as the ratio between live and planted fish.

IoT configuration

The automated monitoring system was designed under a distributed network architecture, oriented to the continuous control of physicochemical variables relevant to the intensive culture of *Oreochromis* spp. Each monitoring node was constituted from an ESP32 microcontroller, which executed the capture and transmission of data from submersible sensors installed in the experimental tanks. A DS18B20 digital temperature sensor, analog sensors for dissolved oxygen (DFRobot SEN0237) and pH (DFRobot SEN0161), and a TSD-10 optical sensor for turbidity were used. All devices were encapsulated in watertight IP65-rated enclosures, and powered by 5V rechargeable batteries, with external power backup.

The nodes communicated with a central base station via WiFi protocol, establishing a local transmission channel without dependence on external infrastructure. In the central server, mounted on a Raspberry Pi 3B+, applications developed in Node-RED were run for data acquisition, comparative analysis with critical thresholds and dynamic visualization using the Grafana system. This architecture allowed recording data in real time with a frequency of 288 records per day for temperature, oxygen and pH, and 96 records per day for turbidity, replicating successful models reported in recent literature **(Plazas & Paz, 2019)**.

To ensure the quality and reliability of the system, sensor calibration procedures were performed before and during the experimental period. The pH sensors were adjusted with standard buffer solutions (pH 4, 7 and 10), while the oxygen sensors were verified by saturation and zero oxygen conditions. Additionally, logic flows were designed in Node-RED for the automatic generation of alerts through Telegram when the monitored variables exceeded the permissible ranges defined for tilapia in intensive systems. This type of implementation significantly reduces the operational response time, improves the traceability of the system and reduces environmental variability, in accordance with the principles established in studies of remote monitoring in sustainable aquaculture **(Merkin *et al.*, 2013)**.

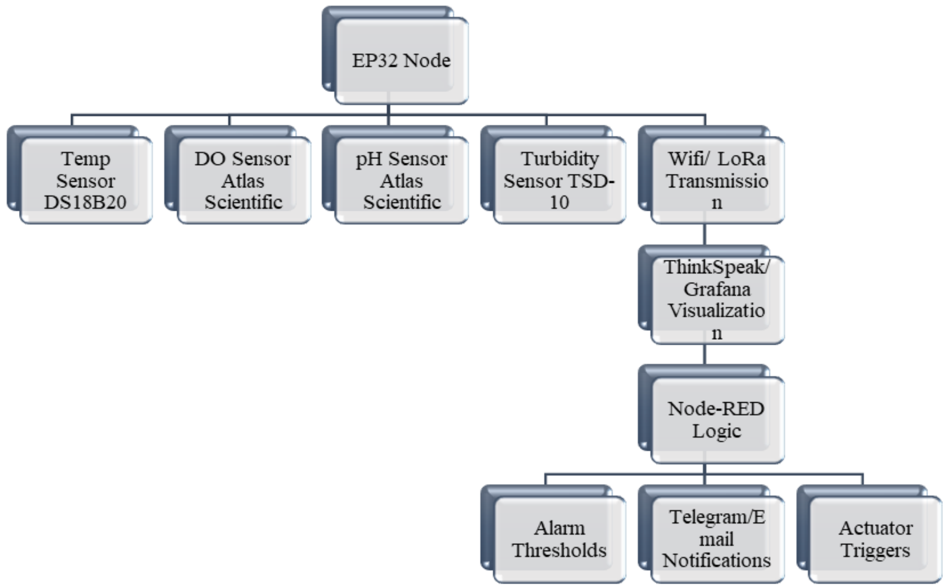

Fig. 2. Flowchart of IoT system for Tilapia RAS culture

RESULTS AND DISCUSSION

Physicochemical parameters of water

Five key physicochemical parameters critical to the health and productivity of *Oreochromis* spp. were evaluated in this study: temperature (TEMP), dissolved oxygen (DIO), pH, total ammonia (TA), and turbidity (T). These variables are essential for regulating physiological functions such as metabolism, respiration, immunomodulation, and feed conversion. Measurements were conducted across three technological levels: T1 (manual control), T2 (continuous digital monitoring), and T3 (IoT-based monitoring with automation).

Fig. (3) presents a radar plot summarizing the mean water quality profile recorded for each treatment.

Temperature (TEMP)—a parameter that directly influences metabolic rate and feed efficiency—remained within the recommended range of 26–30 °C across all treatments **(Bhatnagar & Devi, 2019)**. However, Treatment T3 demonstrated the lowest temperature variability, with a mean of 27.91 ± 0.81 °C, indicating enhanced thermal stability as a result of automated recirculatory control. This improved thermal regulation likely reduced the risk of cumulative heat stress and contributed to more consistent metabolic and growth performance in the system.

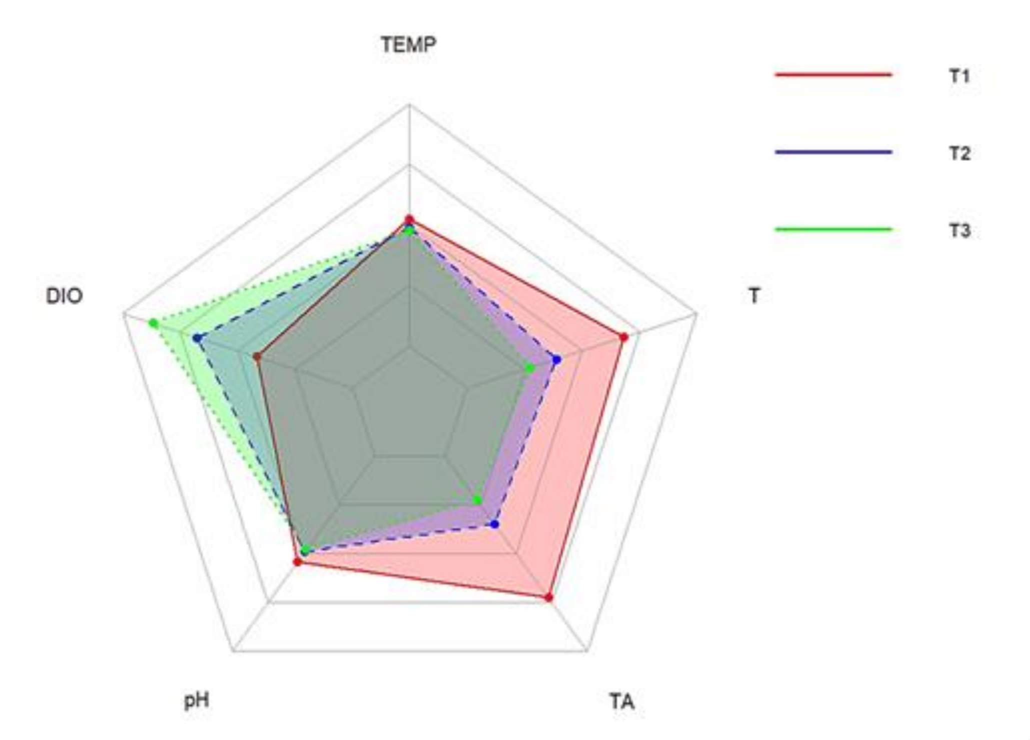

Fig. 3. Radar diagram of water physicochemical parameters

Dissolved oxygen (DIO) at T3 recorded a mean of 5.60 ± 0.24 mg/L, significantly higher than T2 (5.02 ± 0.29) and T1 (4.25 ± 0.36). According to **Boyd (2020)**, values below 5mg/ L affect feed efficiency and behavior. T3 remained consistently within the optimal range (5- 7mg/ L), benefiting from automated activation of aerators in response to critical thresholds. These findings agree with the study of **Wambua *et al.* (2021)**, who demonstrated that IoT systems with control logic substantially improve nocturnal oxygenation in RAS.

In pH, no significant differences were detected between treatments. The average value remained between 7.48 and 7.54, a range considered ideal for tilapia (6.5-8.5) **(El-Sayed, 2006)**. Although treatment T1 presented a slightly higher alkalinity, no associated physiological impact was observed. The pH stability in all systems suggests an adequate balance between CO_2 production, nitrification and buffering capacity of the water, which validates the biochemical efficiency of the system under standardized conditions.

Total ammonia (TA) values showed significant and critical differences. T1 presented the highest concentration (0.39 ± 0.05 mg/L), exceeding the safe threshold of 0.25 mg/L suggested for closed systems **(Boyd, 2020)**. In contrast, T2 (0.24 ± 0.04) and T3 (0.19 ± 0.03) remained within acceptable limits. The lower concentration in T3 is associated with the ability of the system to activate recirculation flows and optimize biofiltration efficiency, which reduces the risk of accumulation of non-ionized NH_3. This pattern coincides with that described by **Soto (2010)**, who validated that sensor-based automatic response logic reduces nitrogen loading peaks.

Finally, turbidity (T), a key indicator of solids accumulation and hydraulic efficiency, also favored T3 (9.1 ± 1.4), followed by T2 (10.8 ± 2.0) and T1 (15.2 ± 3.1). The recommended upper limit for RAS systems is around 15 NTU **(Bhatnagar & Devi, 2019)**. Only T1 exceeded this threshold, suggesting deficiency in passive clarification processes. T3, on the other hand, reflects the effectiveness of recirculation pump automation as a function of suspended solids levels, which favors a more stable environment conducive to natural fish behavior.

Production yield analysis

The productive performance of *Oreochromis* spp. was evaluated using four key zootechnical indicators: weight gain, specific growth rate (SGR), feed conversion ratio (FCR) and survival. Table (1) presents the results with their respective standard deviations and superscript letters indicating significant differences between treatments ($P < 0.05$).

Table 1. Productive performance of *Oreochromis* spp. under three levels of technological implementation

Parameter	T1	T2	T3
Weight gain (g)	184.2 ± 10.1[c]	208.5 ± 12.5[b]	221.9 ± 11.7[a]
SGR (%/day)	2.48 ± 0.09[c]	2.68 ± 0.11[b]	2.78 ± 0.10[a]
FCR	1.84 ± 0.13[a]	1.63 ± 0.12[b]	1.53 ± 0.11[c]
Survival (%)	91.7 ± 2.9[c]	95.6 ± 2.3[b]	97.8 ± 1.5[a]

Weight gain reached its highest value in T3 (221.9 ± 11.7 g), with statistically significant differences compared to T1 and T2. This finding suggests that stable control of physicochemical parameters through sensor-based automation directly influences the anabolic performance of fish. Similar improvements under optimized conditions of oxygenation and temperature have been reported by **Badran *et al.* (2023)**.

In terms of Specific Growth Rate (SGR), T3 also recorded the highest value (2.78 ± 0.10 %/day), confirming that a stable and well-regulated environment reduces metabolic stress and enhances feed utilization efficiency. According to **Santos *et al.* (2019)**, an SGR greater than 2.5 %/day reflects favorable environmental conditions and feed conversion in growing tilapia.

The Feed Conversion Ratio (FCR) was significantly lower in T3 (1.53 ± 0.11), indicating more efficient feed use. This aligns with findings from **Soares *et al.* (2020)**, who demonstrated that sensor-driven feedback feeding systems help minimize overfeeding and reduce water quality degradation. Lower FCR values translate into both economic benefits (through reduced feed costs) and environmental gains (by lowering nutrient waste discharge), particularly important in intensive systems.

Survival rate, a critical indicator of fish welfare and system management, was also highest in T3 (97.8 ± 1.5 %) compared to T1 (91.7 ± 2.9 %). The improved survival is attributed to continuous environmental monitoring and the system's automated response capabilities to adverse conditions such as hypoxia or elevated ammonia. **Badran *et al.* (2023)** reported similar mortality reductions—up to 10%—with the integration of IoT sensors in closed aquaculture systems.

Operational performance of the IoT system

The operational efficiency of the IoT system was assessed using two functional indicators: response time to critical environmental events and the daily frequency of alarm generation. These indicators provide insight into the system's real-time detection capabilities, responsiveness, and scalability within intensive *Oreochromis* spp. culture systems in RAS.

Fig. (3) illustrates the daily mean response time to critical conditions in treatments T2 and T3, comparing a digital monitoring system without automation (T2) and a fully automated system (T3) using programmable logic.

A clearly lower operational latency was observed in T3, indicating higher system responsiveness and management efficiency during environmental fluctuations. This reduced latency validates the functionality of the distributed system architecture, which utilizes ESP32 nodes, Node-RED logic, and LoRa/WiFi wireless communication. These components enable instantaneous interventions during undesirable events such as oxygen depletion or pH imbalance, ultimately reducing the risk of fish mortality **(Cardozo *et al.*, 2024; Medrano *et al.*, 2024)**.

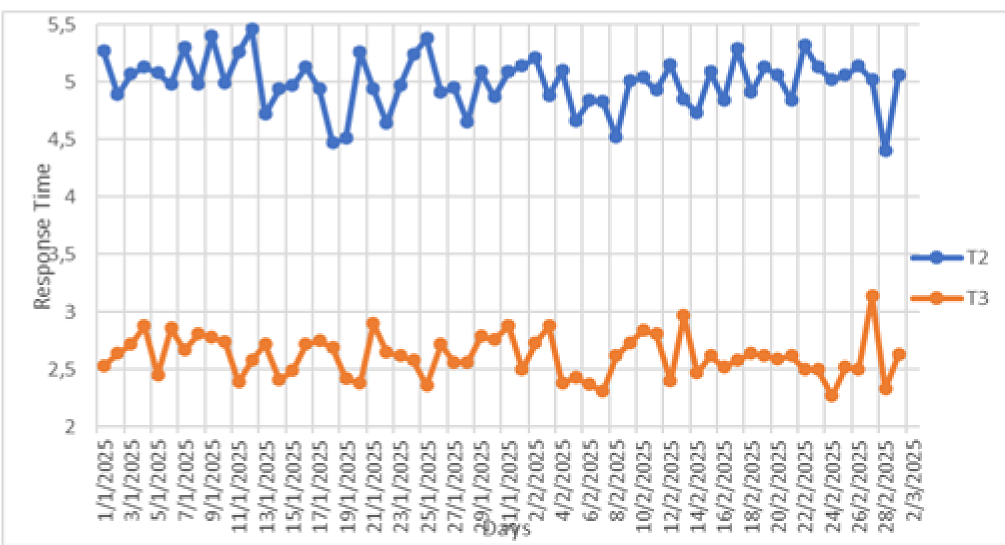

Fig. 3. Daily response time to critical events in treatments T2 and T3.

In Fig. (4), the analysis of the number of alarms generated daily revealed a higher frequency in T3 (≈2.9 alarms/day) compared to T2 (≈1.4 alarms/day). This difference is explained by the higher sensitivity programmed in the advanced system, which includes strict thresholds and higher resolution in sensor reading. According to **Noble *et al.* (2018)**, systems with higher readout resolution and multiple detection logic allow proactive detection of suboptimal conditions before they become critical threats to the crop.

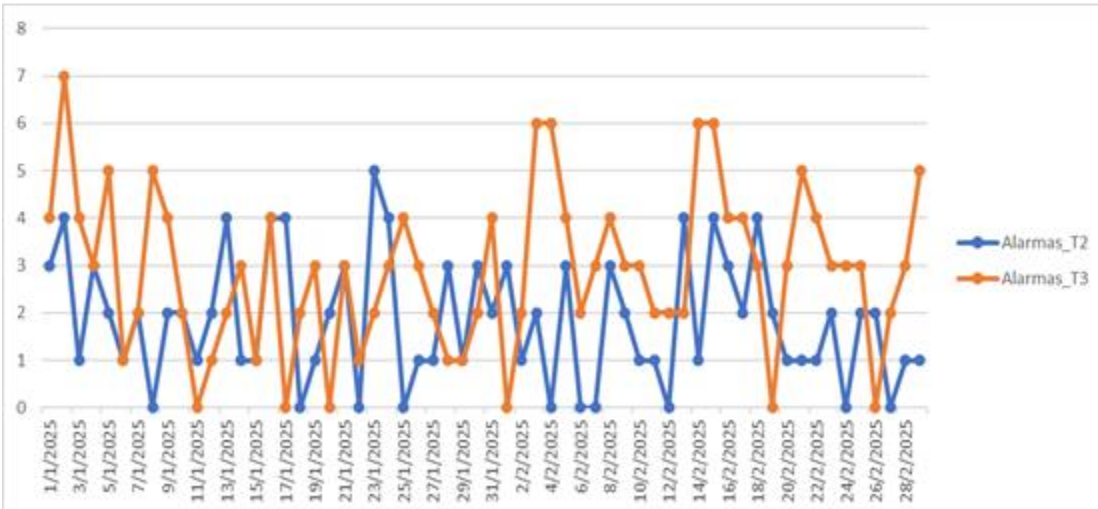

Fig. 4. Number of alarms generated daily in treatments T2 and T3

The high frequency of events in T3, combined with a fast reaction capability, supports its superiority as a preventive system. As highlighted by **Singh *et al.* (2024)**, IoT systems with logical automation have the ability not only to monitor, but also to trigger autonomous responses that optimize resources (aeration, recirculation) and prevent deterioration of water conditions. From a system engineering approach, this behavior is consistent with low-coupling, high-availability architectures that improve operational resilience **(Troell *et al.*, 2014; Chen *et al.*, 2022)**.

LIMITATIONS AND FUTURE PERSPECTIVES

Despite the encouraging results, it is important to recognize certain limitations of the present study. First, the trials were conducted under controlled conditions and at a semi-intensive scale, which could restrict the extrapolation of the results to larger commercial scale operations. In addition, we worked with a single hybrid species of *Oreochromis* spp. and therefore the findings may not be fully representative under different genetic or environmental conditions.

For future research, it is recommended to explore the integration of predictive analytics and artificial intelligence tools that allow not only the early detection of risks, but also the automation of corrective responses. It is also suggested to scale the IoT infrastructure to commercial farms, incorporate biosecurity monitoring modules and evaluate the economic viability in various socioeconomic contexts. Finally, it will be key to strengthening the technical capabilities of operators through training programs that facilitate the digital transition in aquaculture, especially in developing regions.

CONCLUSION

- The integration of Internet of Things (IoT)-based technologies, including real-time sensors and automated control logic, significantly improved the stability of critical water quality parameters such as dissolved oxygen, temperature and ammonium, demonstrating superior environmental regulation compared to manual and semi-automated approaches.
- The advanced IoT system (T3) resulted in better zootechnical performance in *Oreochromis* spp. as evidenced by higher weight gains, greater feed efficiency and higher survival rates. These results validate the effectiveness of technological intensification in semi-intensive aquaculture systems.
- The distributed architecture implemented - based on ESP32 nodes, Node-RED automation and wireless telemetry - proved to be highly efficient in detecting and responding to critical events, reducing operational latency and improving alert generation. This infrastructure supports scalable and resilient aquaculture management models, aligned with the principles of Aquaculture 4.0.

REFERENCES

Badran, M.F.; Griesh, A.Sh.; Ali, M.A.M.; Mouhmed, A.A.Y.; Mahmoud, Y.K. and Yusuf, M.S. (2023). The Effect of Simple Recirculating Aquaculture System (RAS) on Physiological Response, Blood Parameters, and Growth Performance of Nile Tilapia Oreochromis niloticus and Flathead Gray Mullet Mugil cephalus Under Polyculture Condition. https://doi.org/10.21203/rs.3.rs-2600209/v1

Bhatnagar, A. and Devi, P. (2019). Water quality guidelines for the management of pond fish culture. *International Journal of Environmental Sciences, 5*(2). https://doi.org/10.6088/ijes.2013030600019

Boyd, C.E. (2020). *Water Quality: An Introduction.* Springer International Publishing. https://doi.org/10.1007/978-3-030-23335-8

Cardozo Ramírez, L.E.; Calle Viles, E.; Fuentes Tellería, R.; Ramos Silvestre, E.R. and Tavera Gutiérrez, D.F. (2024). Monitoreo de la calidad del agua en criaderos de tilapias mediante tecnologías LPWAN y VPS. *Ciencia Latina Revista Científica Multidisciplinar*, *8*(2), 5609-5629. https://doi.org/10.37811/cl_rcm.v8i2.10975

Chen, C.; Lu, J.; Zhou, M.; Yi, J.; Liao, M. and Gao, Z. (2022). A YOLOv3-based computer vision system for identification of tea buds and the picking point. *Computers and Electronics in Agriculture*, *198*, 107116. https://doi.org/10.1016/j.compag.2022.107116

El-Sayed, A.-F. M. (2006). *Tilapia Culture.* CABI Publishing.

FAO (Ed.). (2022). *Towards Blue Transformation.* FAO.

Le, N.-B.; Woo, H.; Lee, D. and Huh, J.-H. (2024). AgTech: A survey on digital twins-based aquaculture systems. *IEEE Access*, *12*, 125751-125767. https://doi.org/10.1109/ACCESS.2024.3443859

Medrano, K.; Hernández, E.; Tejada, R. and Moreno, A. (2024). Tecnologías IoT para el monitoreo de la calidad del agua en la acuicultura. *European Public & Social Innovation Review*, *10*, 1-16. https://doi.org/10.31637/epsir-2025-929

Merkin, G.V.; Stien, L.H.; Pittman, K. and Nortvedt, R. (2013). Digital image analysis as a tool to quantify gaping and morphology in smoked salmon slices. *Aquacultural Engineering*, *54*, 64-71. https://doi.org/10.1016/j.aquaeng.2012.11.003

Misra, N.N.; Dixit, Y.; Al-Mallahi, A.; Bhullar, M.S.; Upadhyay, R. and Martynenko, A. (2022). IoT, Big Data, and Artificial Intelligence in agriculture and food industry. *IEEE Internet of Things Journal*, *9*(9), 6305-6324. https://doi.org/10.1109/JIOT.2020.2998584

Nairuti, R.N.; Munguti, J.M.; Waidbacher, H. and Zollitsch, W. (2021). Growth performance and survival rates of Nile tilapia (Oreochromis niloticus L.) reared on diets containing Hermetia illucens larvae meal. *Die Bodenkultur*, *72*(1), 9-19. https://doi.org/10.2478/boku-2021-0002

Naylor, R.L.; Hardy, R.W.; Buschmann, A.H. et al. (2021). A 20-year retrospective review of global aquaculture. *Nature*, *591*(7851), 551-563. https://doi.org/10.1038/s41586-021-03308-6

Noble, C.; Gismervik, K.; Iversen, M.H.; Kolarevic, J.; Nilsson, J.; Stien, L.H. and Turnbull, J.F. (2018). *Welfare Indicators for Farmed Atlantic Salmon: Tools for Assessing Fish Welfare.* 351pp.

Piamba-Mamian, T.M.; Zambrano, L.E.; Montaño Rúales, L.A. and Rojas Gonzales, F.A. (2020). Implementación de un sistema de monitoreo IoT aplicado a una piscicultura de trucha. *Informador Técnico*, *85*(1). https://doi.org/10.23850/22565035.2937

Plazas Pemberthy, L.A. and Paz Ruiz, N.E. (2019). Diseño e implementación de un sistema de monitoreo de parámetros de calidad de agua en cultivo de tilapia. *Publicaciones e Investigación*, *13*(2), 11-22. https://doi.org/10.22490/25394088.3255

Pulkkinen, J.T.; Kiuru, T.; Aalto, S.L.; Koskela, J. and Vielma, J. (2018). Startup and effects of relative water renewal rate on water quality and growth of

Oncorhynchus mykiss. *Aquacultural Engineering*, *82*, 38-45. https://doi.org/10.1016/j.aquaeng.2018.06.003

Ricker, W.E. (1979). Growth rates and models. In: *Fish Physiology*, *Vol. 8*, pp. 677-743. Elsevier. https://doi.org/10.1016/S1546-5098(08)60034-5

Rodríguez-Hernández, M.E.; Martínez-Castellanos, G.; López-Méndez, M.C.; Reyes-Gonzalez, D. and González-Moreno, H.R. (2025). Production costs and growth performance of Oreochromis niloticus in intensive systems. *Sustainability*, *17*(4), 1745. https://doi.org/10.3390/su17041745

Santos, J.F.; Assis, C.R.D.; Soares, K.L.S.; Rafael, R.E.Q.; Oliveira, V.M.; De Vasconcelos Filho, J.E.; França, R.C.P.; Lemos, D. and Bezerra, R.S. (2019). Comparative study on Oreochromis niloticus under different systems. *Aquaculture*, *503*, 128-138. https://doi.org/10.1016/j.aquaculture.2018.12.044

Shi, B.; Sreeram, V.; Zhao, D.; Duan, S. and Jiang, J. (2018). Wireless sensor network-based monitoring for fishpond aquaculture. *Biosystems Engineering*, *172*, 57-66. https://doi.org/10.1016/j.biosystemseng.2018.05.016

Soares, M.; Rezende, P.C.; Corrêa, N.M.; Rocha, J.S.; Martins, M.A.; Andrade, T.C.; Fracalossi, D.M. and Do Nascimento Vieira, F. (2020). Wireless sensor network-based monitoring for fishpond aquaculture. *Biosystems Engineering*, *172*, 57-66. https://doi.org/10.1016/j.aqrep.2020.100344

Soto Zarazúa, G. (2010). *Sistema Integral de Automatización para Sistemas de Producción Intensiva Acuícola*. Doctoral Thesis, Universidad Autónoma de Querétaro. https://ri-ng.uaq.mx/bitstream/123456789/833/1/RI003939.pdf

Terjesen, B.F.; Summerfelt, S.T.; Nerland, S.; Ulgenes, Y.; Fjæra, S.O.; Megård Reiten, B.K.; Selset, R.; Kolarevic, J.; Brunsvik, P.; Bæverfjord, G.; Takle, H.; Kittelsen, A.H. and Åsgård, T. (2013). Design and performance of a facility for RAS research. *Aquacultural Engineering*, *54*, 49-63. https://doi.org/10.1016/j.aquaeng.2012.11.002

Troell, M.; Naylor, R.L.; Metian, M.; Beveridge, M.; Tyedmers, P.H.; Folke, C.; Arrow, K.J.; Barrett, S.; Crépin, A.-S.; Ehrlich, P.R.; Gren, Å.; Kautsky, N.; Levin, S.A.; Nyborg, K.; Österblom, H.; Polasky, S.; Scheffer, M.; Walker, B.H.; Xepapadeas, T. and De Zeeuw, A. (2014). Does aquaculture add resilience to the food system? *Proceedings of the National Academy of Sciences*, *111*(37), 13257-13263. https://doi.org/10.1073/pnas.1404067111

Wambua, D.M.; Home, P.G.; Raude, J.M. and Ondimu, S. (2021). Environmental and energy requirements for Nile tilapia in RAS. *Aquaculture and Fisheries*, *6*(6), 593-600. https://doi.org/10.1016/j.aaf.2020.07.019

Zuñiga Jara, S. and Goycolea, M. (2014). Bioeconomic model for red tilapia on the coast of Ecuador. *Aquaculture International*, *22*, 339-359.