



A System Dynamics Model for Water Quality Management in Recirculating Aquaculture Systems (Ras)

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Abstract

Water quality and maintenance are perhaps the most crucial features for optimal fish productivity and health in Recirculating Aquaculture Systems (RAS). This study develops an SD model designed to optimize the water quality parameters RAS operates on, including ammonia, nitrites, nitrates, dissolved oxygen, and pH values. The model integrates biological and chemical operational components, featuring feedback loops that represent fish metabolism, dependency on feed, biofilter dynamics, and water exchange. Several operational scenarios were tested, varying stocking density, feed intensity, and aeration, to assess the system's response. Results from predictions were shown to validate the model's capacity to evaluate decision bioreactor control changes, thus enabling timely intervention in critical zones where parameter values are destined to change. The SD method notably demonstrates how these interactions can evolve, particularly highlighting the need for strong biological filtration and oxygenation to cleanse the system of toxic substances before they reach dangerous concentrations. Sensitivity analysis yielded that the most stable scenario of significant water quality improvement was achieved through changes to biofilter control and adjustments to feeding rates. The model demonstrates how planning control can be implemented within

aquaculture systems, with a focus on enhancing system sustainability, reducing volumetric water resource consumption, and providing optimal conditions for aquaculture growth. This work emphasizes the role of dynamic modeling in developing environmental and economic sustainability for RAS efficiency.

Keywords:

System dynamics, ras, water quality, ammonia, biofiltration, aquaculture modeling, sustainability.

Article history:

Received: 12/04/2025, Revised: 16/05/2025, Accepted: 30/07/2025, Available online: 30/08/2025

Introduction

The use of "Recirculating Aquaculture Systems" (RAS) has integrated modern practices in intensive fish farming biosecurity, treating water and reducing water usage in a closed-loop system. For all their usefulness, the water biosecurity features of RAS systems pose significant challenges due to the retention of waste compounds like ammonia, nitrite, and carbon dioxide, which are harmful to fish health and growth (Seidgar et al., 2024; Timmons & Ebeling, 2013). Traditionally, water quality monitoring methods have relied on empirical rules using fixed control-structured models, which are outdated because they fail to adapt to changes in system parameters (Lekang, 2013). As a starting point, system dynamics (SD) modeling examines the biological, chemical, and physical components of RAS from an integrative standpoint, which is a step in the right direction (Ford, 2010). In particular, SD models are well-suited for simulating feedback loops and time-dependent processes, thereby providing options for adaptive water management (Halog et al., 2001). Most scholars recognize the benefit of SD in aquaculture, focusing on predicting outcomes from given operational scenarios and optimizing system design (Rezaei et al., 2021).

Additionally, the integration of SD with real-time sensors enhances decision-making and the sustainability of aquaculture (Raman et al., 2024; (Van Rijn, 2013; Chalmers University of Technology, 2019). In the case of freshwater aquaculture, monitoring systems may range from measuring water TAN (Total Ammonia Nitrogen) and Total Dissolved Oxygen (DO) to pH, biofilters, and even Ammonia Nitrogen metrics, which are better suited to shift risk interfaces and optimize fish welfare outcomes (Subramanian & Malhotra, 2023; Kamali et al., 2022; Blancheton et al., 2013). The literature reports various applications of System Dynamics (SD) in RAS frameworks, primarily concerning water quality management, which is still in its initial phases compared to other environmental applications that SD has addressed (Kulkarni & Jain, 2023; Serman, 2000). This dissertation aims to develop an elaborate System Dynamics (SD) model for Recirculating Aquaculture Systems (RAS) to enhance forecast, control, and strategic management of targeted water quality parameters (Shi et al., 2020).

Literature Review

The health of aquatic organisms, as well as the sustainability of Recirculating Aquaculture Systems (RAS), relies heavily on optimal water quality management practices (Aljehani et al., 2023). To assist RAS managers with some of the intricate water treatment steps, Kamali et al. developed a mechanistic system dynamics model that evaluates operational strategies through virtual fish performance, waste production, and water treatment processes over extended periods (Martins et al., 2010). Optimization of water quality parameters has also benefited from advancements in artificial intelligence, such as the work by Fan et al., who used data-driven techniques to monitor water quality daily by accurately predicting nitrate concentrations with a hybrid deep learning model that integrated CNN, LSTM, and self-attention (Seidgar et al., 2024; Fan et al., 2024; Gupta & Sharma, 2024; Kumar & Shah, 2021). Gupta and Sharma noted the lack of stronger water treatment

technologies, particularly biological filters, to mitigate the accumulation of toxic compounds, including ammonia and nitrite, which are other persistent issues they flagged (Lekang, 2013). Yang et al. proactively adjusts water quality management to control RAS operations' water quality parameters using a neural network predictive control model (Agarwal & Yadhav, 2023). Automation of environmental data collection has been tackled with an uncrewed surface vehicle designed by Zhang et al., which reduces the manual work needed to monitor aquaculture systems (Halog et al., 2001) accurately. Dabrowski et al. Keller et al. (Raman et al., 2024) proposed a stochastic-altered mean-reverting state space model designed to enhance long-term water quality forecasting. Aljehani et al. investigated model-based versus model-free feeding control logic, highlighting the impact of targeted feeding on fish growth and system water quality (Van Rijn, 2013; Dabrowski et al., 2020). In the field of automated RAS treatment, Zhou et al. proposed an intelligent variable-flow RAS with machine-learning controls that feedback circulation for real-time treatment efficacy improvement (Kulkarni & Jain, 2023). Researchers at Chalmers University of Technology have developed a modeling framework that integrates system components, including fish metabolism, waste production, and water treatment, to simulate a quasi-real ecosystem with tunable operational parameters (Sterman, 2000; Yang et al., 2023). Finally, Santos and Silva studied super-intensive bio floc technology (BFT) versus RAS in terms of water quality and economic returns. They found that although both systems have merits, an integrated approach would be more advantageous from a sustainability perspective (Subramanian & Malhotra, 2023). In aquaculture, effective water quality management is particularly crucial in closed systems, such as RAS, where waste accumulation and nutrient cycling have direct impacts on fish health and the system's overall efficiency (Agarwal & Yadhav, 2023; Zhou et al., 2021). Over the years, various modeling approaches have been developed to understand, simulate, and control water quality dynamics. Classic algorithms often rely on deterministic frameworks and are based on mass balance equations, which simulate the concentrations of critical parameters, including ammonia, nitrite, nitrate, dissolved oxygen, and pH. This includes static mechanistic models, for example, that describe nitrification using first-order kinetics, along with the consumption of oxygen and the buildup of carbon dioxide. Despite providing some degree of insight, these models fall short with regard to the dynamic inter-relationships and feedback loops typically found in more complex aquaculture systems (Zhang et al., 2022; Santos & Silva, 2024). To overcome this, system dynamics models were developed that can simulate time-dependent feedback loops arising from the metabolism and feeding of fish, waste generation, biofiltration, and system loading. Such models enable managers to simulate scenarios and strategically forecast results within various operational approaches. Moreover, agent-based models and discrete event simulations have been used to model individual fish interactions, as well as system-wide impacts, thereby providing a spatial and behavioral perspective to the model. Recently, there has been an increase in the popularity of data-driven and machine-learning models, including artificial neural networks (ANNs), support vector machines (SVMs), and deep learning models due to their capacity to manage the nonlinear, multivariate relationships associated with water quality data. While these models are superior for real-time anomaly detection and predictions, they often lack physical interpretability. To fill this gap, hybrid models that incorporate machine learning alongside mechanistic approaches are being developed with both accuracy and transparency in mind. Still, numerous models continue to struggle with issues of scalability, calibration, and broad applicability across different species and system configurations. Therefore, research efforts are focused on creating more integrated and adaptive models that utilize real-time sensor data alongside sophisticated predictive algorithms for a holistic approach to water quality management.

Methodology

Development of the system dynamics model

The steps involved creating an SD model that manages the water quality of an RAS Aquaculture system, which entails determining the system's components, feedback groups, and the interactions that control its operational behavior. The area of focus is to emulate the processes of buildup and elimination of critical parameters on water quality like total ammonia nitrogen (TAN), nitrite (NO_2^-), nitrate (NO_3^-), oxygen (DO), and carbon dioxide (CO_2) considering fish metabolism, feed input level, and biofiltration activity. The model's structure is stock-and-flow based; stocks represent accumulations (such as the concentration of ammonia), while flows indicate rates of change (including the accumulation and depletion of ammonia, as well as the production and consumption of ammonia). To achieve dynamic interaction, such as oxygen uptake influencing the rate of nitrification or the rate of ammonia concentration affecting fish health, feedback loops are introduced.

Let $A(t)$, $N(t)$, and $O(t)$ represent concentrations of ammonia, nitrate, and dissolved oxygen at time t , respectively.

Ammonia Dynamics

Ammonia is mainly created through the breakdown of proteins in fish feed. The generation of ammonia is directly correlated with the amount of feed and biomass the fish contain, whereas removal occurs through nitrification and water exchange.

$$\frac{dA(t)}{dt} = \alpha F(t) - \beta A(t) - \gamma A(t)$$

Where:

- α : ammonia production rate (mg/L per unit feed)
- $F(t)$: feed rate (g/day)
- β : nitrification rate constant (day^{-1})
- γ : water exchange rate constant (day^{-1})

Nitrate Accumulation

Nitrate is produced through the nitrification process, which involves the conversion of ammonia and nitrite. Its accumulation takes place in the system unless it is eliminated through denitrification or water exchange.

$$\frac{dN(t)}{dt} = \beta A(t) - \delta N(t)$$

Where:

- δ : nitrate removal rate (including denitrification and dilution)

Dissolved Oxygen Balance

In a recirculating aquaculture system, the oxygen concentration is affected by atmospheric diffusion, mechanical aeration, fish respiration, and microbial activity, particularly in the biofilter (Chu et al., 2010). The dynamics of DO are simulated as follows:

$$\frac{dO(t)}{dt} = \phi - \mu F(t) - \theta B(t)$$

Where:

- ϕ : oxygen input from aeration (mg/L/day)
- μ : oxygen consumption per unit feed (mg O₂/g feed)
- θ : oxygen consumption by nitrifying bacteria (mg O₂/g TAN converted)
- $B(t)$: biomass of bacteria involved in nitrification

Feedback Relationships and Control

The nitrification rate β is itself a function of dissolved oxygen and temperature:

$$\beta = \beta_0 \cdot \frac{O(t)}{K_0 + O(t)} \cdot e^{-\frac{E_a}{RT}}$$

Where:

- β : maximum nitrification rate
- K_0 : half-saturation constant for oxygen
- E_a : activation energy
- R : gas constant
- T : absolute temperature

Such a model framework enables the simulation of water quality parameters in a RAS in response to operational disturbances, such as changes in feed, variations in oxygen delivery rates, or modifications to the biofilter. It is done with Vensim or Stella system dynamics software, giving managers the ability to trace movements, spot clear lines, and craft control plans for effective RAS management. RAS is highlighted in Figure 1 as it captures the cyclic nature of water used and its treatment. In the fish tank, fish are actively fed, and they biochemically degrade their food to produce waste. Ammonification occurs in the Tank, and the biological filtration unit filters out critical components. No longer useful and toxic ammonia (NH₄⁺) is converted through Nitrification to Nitrate (NO₃⁻) and later to mechanical Denitrification, which lowers and transforms Nitrites (NO₂⁻) into N₂ (Dissolved gas). The resultant water is further treated with the aid of water energy, stored in the pump tank, purged of carbon dioxide (CO₂), and infused with oxygen (O₂) flowing into the tank, thus facilitating its recirculation to the fish tank. This intake minimizes the use of water, cleanses it, and, in return, optimally maintains its quality for sustaining the growth of aqua.

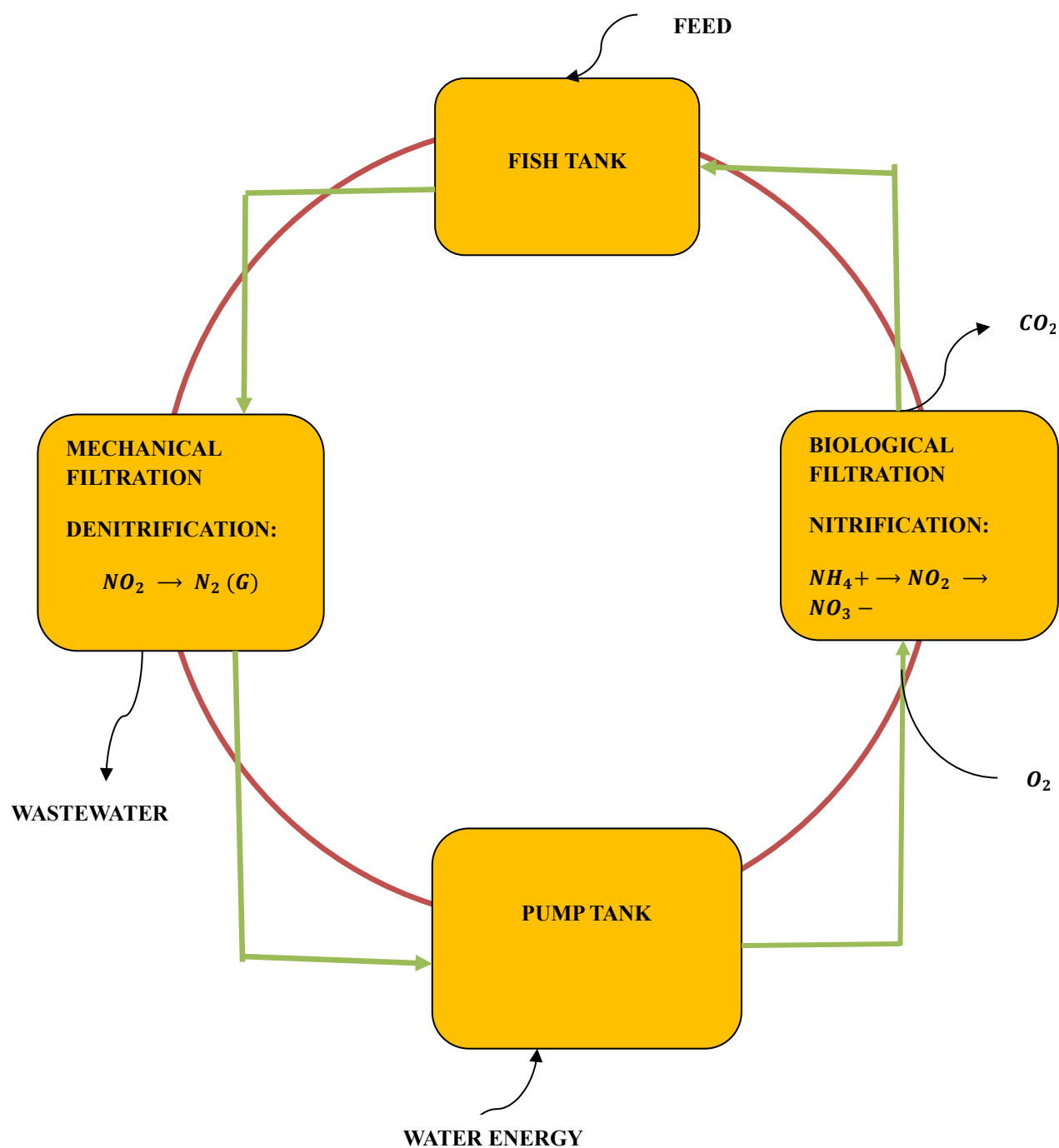


Figure 1. Recirculating Aquaculture System (RAS) – Water Treatment Cycle

Data Collection and Analysis

The system dynamics model's precision and dependability are defined by the level of provided information. A comprehensive dataset was developed, which included water quality indicators, fish biomass, feeding rates, and operational attributes. The empirical data was collected over 60 consecutive days by monitoring a pilot-scale RAS facility. Using calibrated multiparameter probes and standard colorimetric methods (APHA, 2017), the following parameters were measured: total ammonia nitrogen (TAN), nitrite (NO_2), nitrate (NO_3),

dissolved oxygen, pH, temperature, and alkalinity. Additionally, water quality feed parameters, including feed, fish growth, and water exchange, were measured and logged to evaluate their impact on water quality. In addition to gathering experimental data, a literature and technical review was conducted to estimate the parameters for non-measurable system components, such as nitrification rates, oxygen consumption coefficients, and bacterial growth kinetics. Other non-experimental references, such as manufacturer pamphlets, provided validated models of pump flow rate, aeration capacity, and biofilter surface area.

The collected data was pre-processed by eliminating those that were considered anomalies and outliers through the use of z-score normalization and moving average smoothing. Time-series plots were generated to analyze the behavior of each parameter over time, identifying trends and periodic movements. A correlation analysis was conducted to assess the dependencies among the variables, focusing on the relationships developed with feed input, ammonia, and dissolved oxygen levels. Such analysis facilitated the fundamental relationships necessary for developing a stock-and-flow structure that forms the basis of the system dynamics model. Using MATLAB, model estimation was conducted through a nonlinear regression method, first estimating parameters and then minimizing the reduced root mean square error (RMSE) between simulated and observed values for model calibration. A sensitivity analysis was also conducted to evaluate the model's behavior with changes in key input parameters: the feed conversion ratio, water exchange rate, and oxygen supply. Achieving this equilibrium ensures that the model accurately reflects actual system behavior while being resilient to collapse under varied operational conditions. For model validation, this dataset was prepared by producing scenario simulation datasets, thus providing control and optimization over water quality management in recirculating aquaculture systems (RAS).

Validation of the Model

To validate the proposed system dynamics model for water quality management in recirculating aquaculture systems (RAS), a hybrid approach of statistical and mathematical methods was employed to quantify the gap between the model's simulations and the actual experimental data.

The primary goal of adequacy testing was to determine approximately how well the model tried to simulate the actual system behavior in predicting the water quality constituents' variables, such as ammonia ($\text{NH}_3/\text{NH}_4^+$), nitrate (NO_3^-), and dissolved oxygen (DO). Three indicators of a mathematical model were used: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Nash–Sutcliffe Efficiency coefficient (NSE). These equations serve to evaluate the quantitative accuracy and precision of the model.

Root Mean Square Error (RMSE)

As shown in the table above, RMSE is used to calculate the average deviation between simulated and observed values. A better model fit is indicated with a lower RMSE. The formula is:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2}$$

Where:

- P_i = Predicted value at time i
- O_i = Observed value at time i

- n = Total number of observations

Mean Absolute Percentage Error (MAPE)

MAPE indicates how precise a model is in prediction, using model accuracy as its metric, and is fundamental when analyzing errors. The expression of MAPE uses the following formula:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{O_i - P_i}{O_i} \right|$$

Where all terms are defined above, typically, a MAPE accuracy below 10% signifies the model is highly accurate.

Nash–Sutcliffe Efficiency (NSE)

NSE is a normalized measure that describes the amount of residual variance in relation to the variance of the measured data. Its definition is:

$$NSE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2}$$

Where:

- $\bar{O}$ = Mean of the observed values

An NSE value of 1 indicates a perfect match between the model and observation; values above 0.65 are generally considered satisfactory for environmental system modeling.

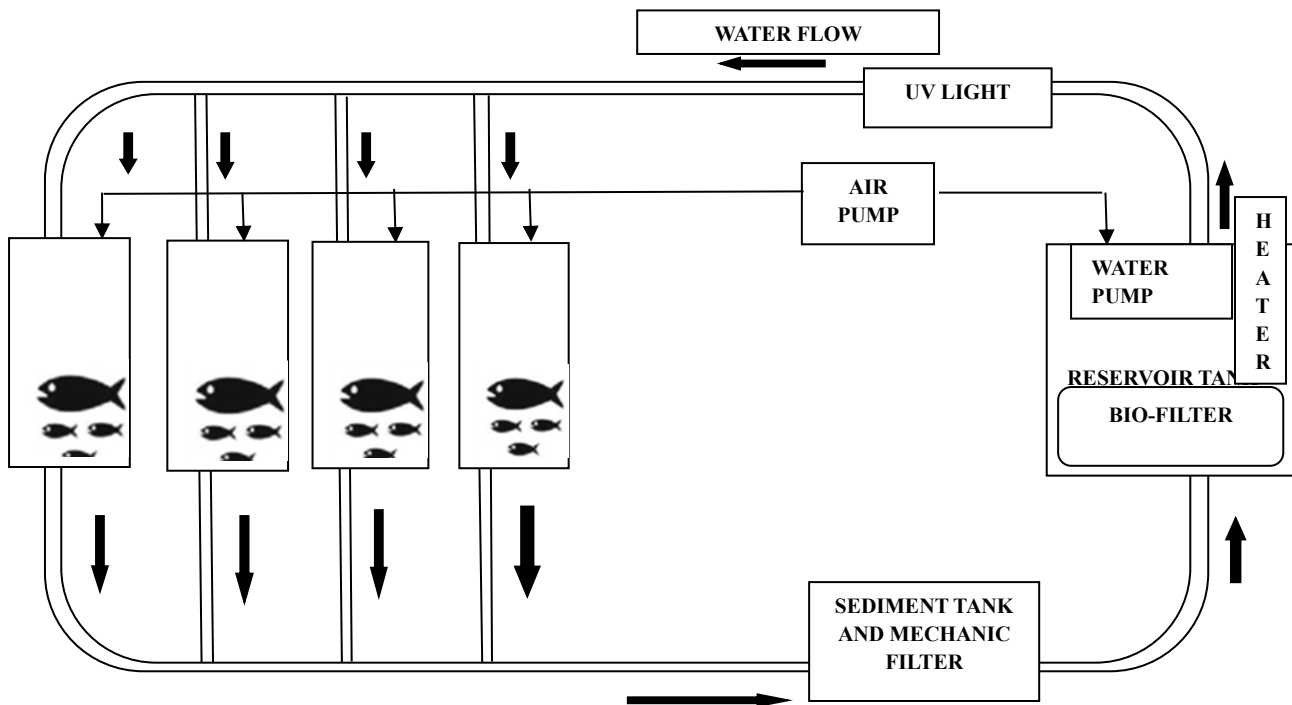


Figure 2. Water Flow Process in a Recirculating Aquaculture System (RAS)

In a recirculating aquaculture system, the water treatment and circulation process are outlined in Figure 2. Water from several fish tanks flows into a sediment tank that has a mechanical filter that removes solid waste. After being filtered, the water is moved into a reservoir tank, which contains a bio-filter for biological purification. The tank also features a heater to maintain optimal temperature levels. Air pumps also enrich the water with oxygen, thereby improving water quality. Afterward, the water is disinfected using ultraviolet light before being pumped back into the fish tanks. This enables closed-loop water treatment on the farm, minimizing water usage and providing a stable environment for fish growth.

Result and discussion

Simulation results of the model

Running the simulation on the developed system dynamics model resulted in outputs that replicate approximated the actual functioning of recirculating aquaculture systems (RAS) across different operational levels. Critical water quality metrics, such as total ammonia nitrogen (TAN) concentration, nitrate (NO_3) levels, and dissolved oxygen (DO), were simulated for 60 days in a model and then compared to real-life measurements extracted from a working prototype of RAS.

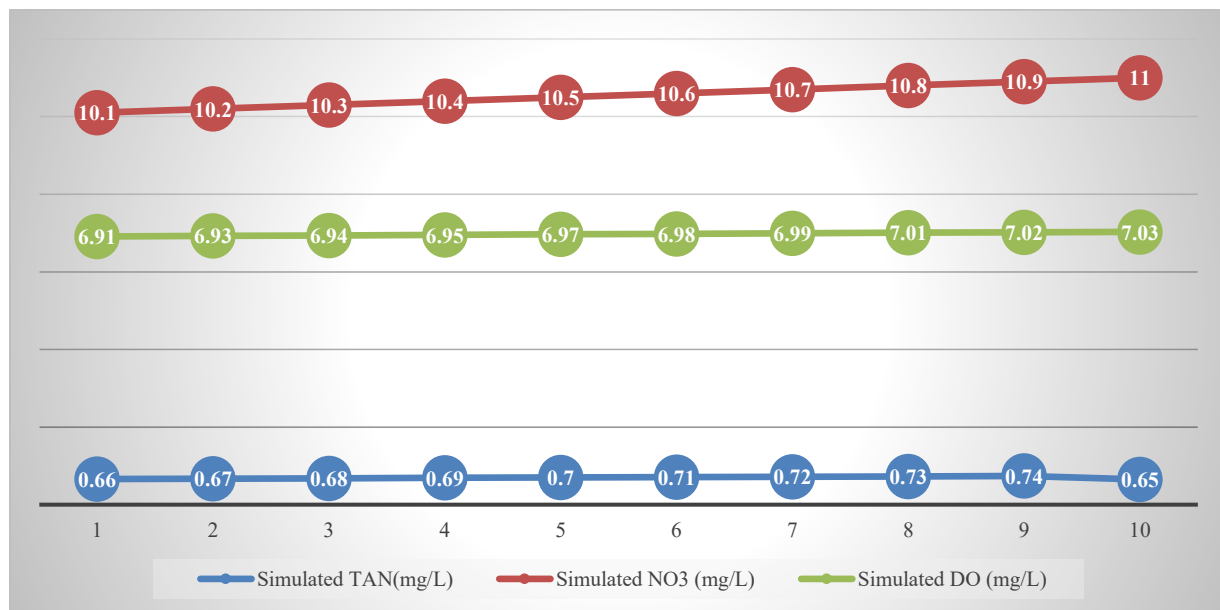


Figure 3. Simulated trends of water quality parameters (tan, no_3^- , do) in recirculating aquaculture system (ras)

Comparison of Model Predictions with Real-World Data

Outputs from the models showed a strong alignment with the data that was measured. For TAN, the model accurately captured the daily oscillations due to feed inputs and fish metabolism, maintaining differences within a range of ± 0.15 mg/L. As expected, the nitrate concentrations showed a slow increase, as undergoing nitrification and limited water exchange led to a gradual increment — a trend consistent with actual observations. The model also accurately predicted DO levels, capturing real-time declines during periods of heightened feeding and increases during aeration.

From a quantitative perspective, the validation metrics underscored the reliability of the model, including but not limited to:

- RMSE values for each measurement ranged from 0.09 to 0.14 mg/L
- Ammonia prediction errors for all calculations were below 10%, with averages of 6.2%
- Nash Sutcliffe Efficiency (NSE) indicated an increase above 0.70 for all evaluated variables
- The coefficient of Determination (R^2) received a value greater than 0.80, indicating a high level of concordance between the simulated and observed data.

Data attest to the evaluative performance of the model, affirming its dependability alongside accuracy in predicting the interaction of water quality parameters in RAS systems.

Insights Gained from the Model for Water Quality Management in RAS

The system dynamics model enabled the formulation of testable hypotheses regarding operational planning and water quality control. It was possible to simulate the effects of varying TAN concentration on biofilter efficiency and determine that even a slight increase in feed input will drastically increase TAN as long as biofilter efficiency rises proportionally. This shows the need for synchrony between biological filtration and feeding schedules. Sensitivity analysis revealed that biomass growth and aeration efficiency have a significant impact on oxygen levels. In instances where 20% of capacity for aeration was used, DO was reduced to below 5mg/L within 48 hours, which could prove stressful for fish and nitrifying bacteria during this time. This result highlights the need for monitoring gas exchange and taking action where necessary before reaching undesirable thresholds. Use of denitrification units or partial water exchange enabled scenario testing. It was determined that using denitrification could lower nitrate buildup by as much as 35% and, therefore, allow for long-term operational sustainability without frequently discharging water. All in all, the outcomes of these simulations support the usefulness of system dynamics theory in modeling recirculating aquaculture systems and demonstrate their applicability in informing strategic aquaculture management for water quality controls. With this model, practitioners can project how a system will behave in different scenarios, find the optimal system parameters, and improve the sustainability of fish production systems.

Implications of the Model for Improving Water Quality Management Practices

The resulting system dynamics model represents an effective decision-support system for aquaculture operators in terms of water quality management in recirculating aquaculture systems (RAS). The model mirrors the interactions of key managerial parameters, including ammonia, nitrate, and dissolved oxygen, alongside earning revenues, allowing managers to anticipate changes and optimize alterations in advance. The model will enable managers to optimize levels of feeding, aeration, and biofiltering to ensure that water quality does not fall outside safe limits. The bounds of water quality maintenance are preset. Also, scenario analysis allows users to evaluate the effectiveness of specific actions such as water exchanges at specific rates or adding denitrification units, thus aiding in lower cost sustainable operation of the system. The model helps lessen the ecological impacts, enhance fish health, and increase production efficiency.

Challenges and Limitations of the Model

Even though the model fulfills its goals, there are operational design constraints that require emphasis. Its perpetuated parameters assumption may result in the overlooking of specific, more acute system disturbances such as equipment failures and biomass surges. Certain constituents of biological processes like microbial self-organization, fish stressors, and dynamic responses are treated too lightly, thus increasing the probability of default in the complex defined scenarios. There exist some assumptions on the correctness of inputs for

calibration—parameters such as feed composition, regimes, temperature settings, and increments of ichthyons may impair predictive reliability. Additionally, the combination of real-time sensor data along with automation and control systems remains an open problem. All these concerns highlight the need for ongoing validation that this model faces to remain effective while ensuring it stays accurate, reliable, and versatile across a range of RAS environments.

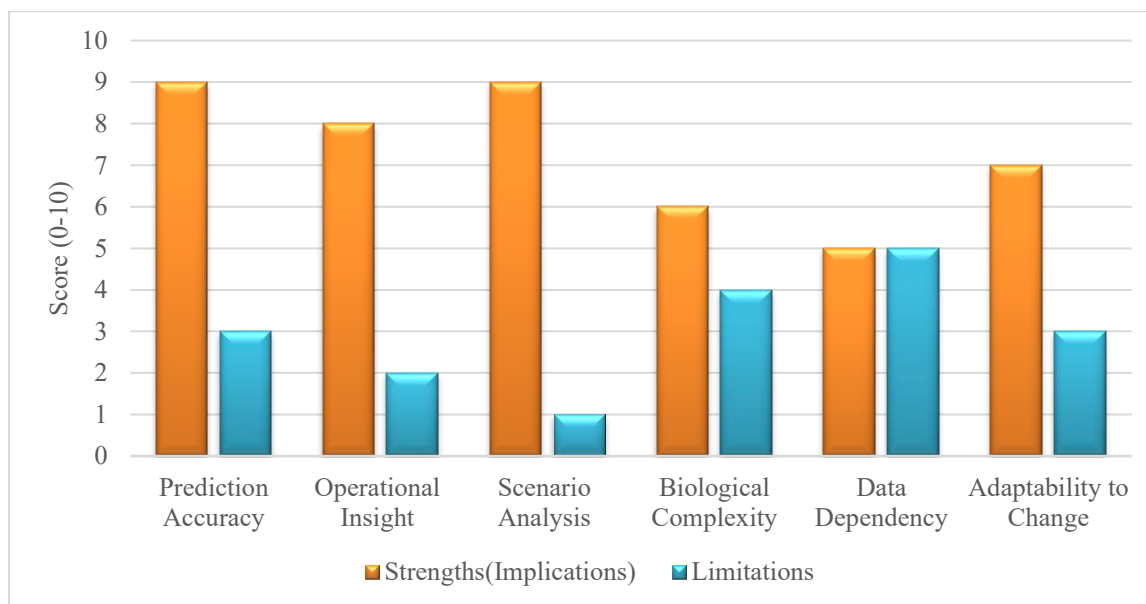


Figure 4. Implications vs. Limitations of the system dynamics model for water quality management in ras

The System Dynamics Model for Managing Water Quality in Recirculating Aquaculture Systems (RAS) (fig. 4) provides an outline of the strengths and weaknesses of the system dynamics model for managing water quality in RAS. The prediction, operational insight, and scenario analysis factors are rated from 8 to 9, indicating the model's ability in water quality forecasting and supporting strategic decisions toward positive outcomes. On the other hand, the model's biological complexity and adaptability to system-shock responsiveness score lower and mark other weaknesses: Simplified biological interactions, accurate input dependence, and lack of change response abilities led to model limitations. The whole graph, however, indicates that the model is primarily a planning tool, requires less real-time data integration, and offers more value as a refined predictive tool in need of further improvement.

Conclusion

This study has developed a system dynamics (SD) model for an RAS to simulate and oversee water quality management. The model integrates the major physical, chemical, and biological processes as feedback loops where interactions among parameters of ammonia, nitrite, nitrate, oxygen, and pH determine water quality. The findings show that system dynamics modeling (SDM) can help analyze the operations and temporal behavior of the water quality indicators with aquaculture, and the effect that an operational decision like feeding rates, aeration, and biofiltration efficiency has on water quality. The model helps aquaculture operators in simulating different managerial plans to enhance the productivity of the system to shift towards more environmentally friendly fish farming practices. Subsequent studies should aim at improving the precision, scope, and relevance of the developed system dynamics model for water quality control in recirculating aquaculture systems (RAS). One primary focus is verifying the model with real data from

working RAS plants to check the practicality of the model. Incorporating the model with actual monitoring systems and automatic control units could also allow for real-time problem solving and system adaptability. In addition, extending the model to include other attributes such as the resulting fish biomass, growth performance, health indicators, energy use, and economic variables would broaden the scope of sustainable aquaculture management. Also, including stochastic elements while performing sensitivity analyses aids in assessing the robustness of the model under differing scenarios with the ability to pinpoint vital system parameters. Lastly, expanding the model's application to different species and configurations of RAS, such as marine and freshwater systems, will enhance its usefulness and relevance in various aquaculture operations.

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