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Review Article

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Health Management Techniques for Swimming Crab Under High-Temperature Conditions

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Abstract Against the backdrop of global climate change, the frequent occurrence of marine heatwaves significantly impacts the stability and health of swimming crab (*Portunus trituberculatus*) aquaculture systems; indeed, high-temperature stress has become a critical environmental factor constraining the industry's sustainable development. This paper systematically reviews the mechanisms by which high-temperature environments affect the physicochemical properties of culture water, production performance, and disease incidence, focusing on key physiological responses such as metabolic disorders, heightened oxidative stress, compromised immune function, and intestinal microbial imbalance. Based on this, and addressing the health management needs of swimming crabs under high-temperature conditions, the paper summarizes key technical systems, including water quality regulation and ecological optimization, nutritional and immunological enhancement, and intelligent monitoring with precision control. Furthermore, drawing on case studies from typical high-temperature culture seasons, the paper comprehensively evaluates the effectiveness of these health management measures in improving survival rates, mitigating disease risks, and stabilizing production performance. Research indicates that establishing an integrated health management system—grounded in environmental regulation, centered on nutritional and immunological modulation, and supported by digital monitoring—is an effective strategy for enhancing the heat tolerance and aquaculture resilience of swimming crabs. Future efforts should focus on further elucidating the mechanisms of high-temperature stress, developing precision health management technologies, and integrating intelligent aquaculture systems to drive high-quality, sustainable development of the swimming crab industry amidst climate change.

Keywords Swimming crab (*Portunus trituberculatus*); High-temperature stress; Health management; Climate change; Intelligent aquaculture

1 Introduction

Swimming crab aquaculture, particularly for *Portunus trituberculatus*, has become an important component of coastal aquaculture in East Asia and a high-value segment of the broader crab industry. Farming of *P. trituberculatus* expanded rapidly in east China over the past decade, demonstrating its strong production momentum and growing commercial relevance. At the same time, the global commercial exploitation of swimming crabs has increased markedly, and crab production from fisheries plus aquaculture reached nearly 1.3 million tons in 2015, indicating the substantial scale of the sector. The economic value of swimming crab is further enhanced by premium product forms such as soft-shell crab, which can command high unit prices in retail and restaurant markets, reflecting strong consumer demand and favorable market returns. However, the industrial chain still faces structural constraints, especially because commercial crab culture technology remains relatively incipient and is currently limited to a small number of species and production systems. For *P. trituberculatus* specifically, hatchery seed production still depends heavily on wild-caught broodstock, which creates a potential bottleneck for long-term industry sustainability and increases vulnerability in the supply chain.

High-temperature environments have become one of the most serious ecological and production challenges facing crustacean aquaculture under ongoing climate change. Rising water temperature directly affects the physiology, growth, and survival of aquatic animals, and crustaceans are especially vulnerable because their thermal tolerance is bounded by narrow physiological thresholds (Wang et al., 2025). Reviews of climate change effects on crustacean culture show that elevated temperature can disrupt food intake, moulting, immune response, survival, and broader

ecosystem stability, while also increasing the likelihood of disease outbreaks (Daunde et al., 2025). More generally across aquaculture species, temperatures above thermal thresholds tend to reduce performance, health, and productivity, showing that heat stress is not only an environmental issue but also a direct production constraint (Mugwanya et al., 2022). In crustaceans, prolonged thermal stress also forces trade-offs between survival, growth, and reproduction, meaning that even animals capable of short-term acclimation may still suffer reduced farming performance under sustained warming. These patterns make high-temperature episodes, including marine heat waves and seasonal extremes, a central risk factor for the stability and profitability of crustacean farming systems.

Evidence from physiological and immunological studies further shows that heat stress can undermine crustacean health well before visible mortality occurs, which is particularly important for intensive farming. In decapod crustaceans exposed to simulated heat waves, thermal stress increased protective chaperones, antioxidant biomarkers, and integrated stress indices, indicating poorer health status even when mortality did not immediately rise. In Chinese mitten crab, exposure to 32°C altered haemolymph metabolism, suppressed total antioxidant capacity during later stages of stress, and shifted the intestinal microbiota toward lower abundance of beneficial bacteria and higher abundance of pathogenic taxa (Li et al., 2022). In *P. trituberculatus*, rapid temperature stress significantly altered serum non-specific immune factors, including hemocyanin and multiple antioxidant and hydrolase enzymes, showing that acute temperature increase can cause metabolic maladjustment and profound changes in physiological and immune function. More broadly in shellfish, chronic stress combined with microbial or abiotic pressures increases infectious disease risk and reduces recovery capacity, reinforcing the view that thermal stress acts through a stress-immunity axis rather than through temperature alone (Coates and Söderhäll, 2020).

Against this background, research on health management techniques for swimming crab under high-temperature conditions is both scientifically necessary and practically urgent. Because heat stress affects metabolism, immunity, microbial balance, and survival-related trade-offs, effective management must move beyond simple temperature observation and instead target resilience mechanisms at the organism and farm levels (Wang et al., 2025). Recent reviews indicate that adaptation options for crustacean aquaculture include nutritional regulation, selective breeding, biotechnology, and husbandry optimization, all of which are relevant for developing high-temperature health management programs in swimming crab culture (Mugwanya et al., 2022; Daunde et al., 2025). Cellular stress proteins are also increasingly recognized as useful tools in crustacean health management, because heat shock proteins maintain protein homeostasis under stress and appear to enhance disease resistance and protective immunity when properly induced (Kumar et al., 2022). In addition, work on *P. trituberculatus* broodstock suggests that culture performance can be improved through nutritional optimization, supporting the broader idea that targeted physiological management is feasible in this species. Therefore, studying health management techniques for swimming crab under high-temperature conditions is essential for reducing thermal injury, stabilizing production, and supporting the sustainable development of the swimming crab farming industry in a warming climate (Daunde et al., 2025).

2 Effects of High Temperature on Swimming Crab Farming Systems

2.1 Impact of high temperature on the culture water environment

High temperature alters the physical and chemical stability of culture water, with the strongest effects appearing in dissolved oxygen dynamics and nitrogen metabolism. In crab ponds, dissolved oxygen fluctuates markedly over a 24 h cycle, and bottom waters are more prone to hypoxia because vertical diffusion weakens with depth (Yin et al., 2021). At the same time, higher temperature increases oxygen consumption and ammonia excretion in crabs, which raises the metabolic burden placed on the pond environment and accelerates deterioration of water quality under intensive culture (Liu et al., 2022).

High temperature also interacts with existing pond management constraints, making environmental instability more difficult to control in commercial systems. Survey data from pond aquaculture show that pH commonly remains within a moderate range, whereas ammonia can exceed the national standard across culture systems, indicating that nitrogen accumulation is already a chronic pressure before heat stress is added. Broader aquaculture evidence further

shows that continuous monitoring of temperature, pH, dissolved oxygen, and ammonia improves growth and reduces mortality by enabling rapid detection of abnormal water-quality events, which is particularly relevant during summer heat periods (Zein et al., 2023; Flores-Iwasaki et al., 2025).

2.2 Impact of high temperature on farming production performance

High temperature can accelerate some developmental processes in swimming crab, but this does not translate into uniformly better production outcomes. In off-season breeding, embryonic development became faster as temperature increased, with total development time shortening from 9.43 d at 27°C to 6.88 d at 33°C; however, development at 31°C became asynchronous and embryo mortality increased, showing that excessive warming trades faster development for poorer developmental quality (He et al., 2022). A similar pattern appears during larval culture: development from zoea to megalopa was fastest at 31°C, but survival declined progressively with increasing temperature, and megalopa survival at 33°C dropped to only 2% (Wu et al., 2024).

For juveniles and crablets, production performance generally follows a unimodal temperature response, with moderate warmth supporting growth and thermal excess suppressing feeding efficiency and survival. In juvenile mud crabs, specific growth rate was optimized around 28.5°C–29.7°C, whereas 35°C reduced survival, feed intake, and feed conversion efficiency and increased oxidative stress (Liu et al., 2022). The same tendency has now been reported for *P. trituberculatus* crablets, in which 30°C produced the highest growth, while 34°C reduced ecdysis frequency, slowed growth, and lowered food intake (Macario et al., 2025).

2.3 Farming risks and mortality events induced by high temperature

High temperature raises farming risk not only through direct thermal injury but also by amplifying energetic disturbance during routine culture operations such as handling, grading, and transport. In *P. trituberculatus*, high temperature increased lactate, ADP, AMP, and the ratios ADP/ATP and AMP/ATP, while decreasing ATP and adenylate energy charge, indicating a mismatch between energy demand and supply under thermal stress. When crabs were exposed to air, mortality increased with higher air temperature and longer emersion time, confirming that hot-weather handling can convert routine operational stress into acute survival loss (Lu et al., 2020).

Heat-related farming risk also includes biological losses that emerge when stressed crabs become less resilient to environmental and pathological challenges. Natural farm mortality events in swimming crab have been linked to Decapod iridescent virus 1, with diseased crabs showing slow movement, anorexia, and very high viral loads in gill tissue, illustrating how severe losses can occur once health status collapses in culture populations (Qiu et al., 2023). In parallel, recent crab-behavior synthesis indicates that temperature, dissolved oxygen, ammonia, pH, conspecific interactions, and pathogens jointly shape feeding, sheltering, aggression, and cannibalism, so high-temperature episodes are likely to increase mortality risk through both physiological stress and behavior-mediated system instability (Zhu et al., 2025).

3 Physiological Responses of Swimming Crab to Heat Stress

3.1 Metabolic regulation

High temperature disrupts metabolic homeostasis in *Portunus trituberculatus* by increasing maintenance energy demand and shifting energy use toward short-term survival rather than growth or storage. Under thermal variation, swimming crabs show increased lactate, elevated ADP/ATP and AMP/ATP ratios, and reduced ATP and adenylate energy charge, indicating a mismatch between energy demand and aerobic supply at high temperature. A similar pattern appears behaviorally, because crabs held at warmer temperatures exhibit higher hemolymph glucose and lactate concentrations together with more intense agonistic activity, showing that heat exposure is coupled to accelerated substrate mobilization and greater energetic expenditure (Su et al., 2020).

Heat stress also appears to reallocate energy among metabolic pathways and physiological functions. Multi-omics evidence indicates that elevated temperature activates lipid and amino acid metabolism at moderate warming and then strengthens glycolysis, gluconeogenesis, and neural-related pathways at higher temperature, supporting rapid energy provision for stress-related behavior (He et al., 2025). Evidence from other stress models in the same species

further suggests that when aerobic metabolism becomes constrained, glycogen and lipids are mobilized, fatty acid and amino acid catabolism increase, and anaerobic metabolism becomes more prominent, which is consistent with the metabolic compensation expected under severe heat load (Jiang et al., 2024).

3.2 Oxidative stress and immune function responses

High temperature induces oxidative stress in swimming crab, and the initial physiological response is the activation of antioxidant and non-specific immune defenses. In embryos, increasing temperature caused superoxide dismutase, glutathione peroxidase, total antioxidant capacity, and malondialdehyde to rise first and then fall, with the strongest antioxidant response occurring at 31°C, indicating that protective systems are activated before being impaired at more severe temperatures (He et al., 2022). In adults exposed acutely to 34°C, hemocyanin, POD, CAT, and ACP increased transiently, whereas SOD and AKP declined early, showing that rapid warming can quickly disturb free-radical balance and alter immune enzyme activity.

When heat stress is prolonged or intensified, protective capacity appears to become insufficient, increasing the risk of cellular injury and immune dysfunction. Although direct long-term heat studies in swimming crab remain limited, work on this species under other environmental stressors shows a common trajectory in which antioxidant defense, heat shock response, and other cellular stress pathways are activated initially but can later be overwhelmed, leading to oxidative damage and apoptosis (Jiang et al., 2024). Related crab studies under heat stress support this interpretation: in Chinese mitten crab, ACP and AKP increased during early exposure but fell below control levels later, while total antioxidant capacity declined after 48 h, suggesting that sustained high temperature can convert an adaptive response into physiological exhaustion (Li et al., 2022).

3.3 Gut health and microbial communities

High temperature likely impairs gut health in swimming crab by weakening digestive performance, disturbing barrier function, and altering microbial community structure. In swimming crab embryos and newly hatched larvae, temperatures above 31°C reduced hatching success and were associated with depressed digestive enzyme activities, especially trypsin and cellulase at 33°C, suggesting that excessive warming compromises later digestive capacity and early-life intestinal function (He et al., 2022). Complementary evidence from ocean acidification experiments in *P. trituberculatus* shows that changes in gut bacteria were closely linked with digestion, stress response, immunity, metabolism, survival, and growth, indicating that gut microbial balance is a central component of physiological resilience in this species (Lin et al., 2020).

Evidence from crab heat-stress models further suggests that thermal stress drives intestinal dysbiosis toward a less favorable microbial profile. In Chinese mitten crab, acute heat stress altered intestinal microbial composition, decreasing beneficial taxa such as *Candidatus*, *Hepatoplasma*, and *Marinifilum* while increasing potentially pathogenic bacteria including *Rhodococcus* and *Morganella* (Li et al., 2022). In swimming crab, dietary lauric acid improved peritrophic membrane thickness, upregulated barrier-related factors, increased beneficial taxa such as *Actinobacteria* and *Rhodobacteraceae*, and reduced *Vibrio*, which indirectly supports the view that maintaining intestinal structure and microbiota stability is an important route for mitigating heat-associated physiological damage (Zhan et al., 2024).

4 Major Health Problems and Disease Risks Under High Temperature

4.1 High-temperature-related stress syndromes

High temperature is a primary environmental stressor for *Portunus trituberculatus* because, as a poikilothermic crustacean, its survival and growth are tightly constrained by water temperature (Qian et al., 2024). Acute heat exposure rapidly disturbs physiological homeostasis, causing metabolic maladjustment of free radicals and marked changes in non-specific immune indices such as hemocyanin, SOD, POD, CAT, ACP, and AKP activities.

At the mechanistic level, thermal stress in swimming crab is not only a passive injury process but also a regulated sensory and cellular response. Temperature-responsive TRP channels are broadly activated under temperature challenge, indicating that crabs possess a molecular system for detecting abrupt thermal fluctuations (Qian et al.,

2024). In parallel, Hsp70 in *P. trituberculatus* functions as an inducible stress-related molecule linked to innate immune defense, supporting the view that heat stress can shift the animal into a protective but energetically costly stress-response state.

4.2 Risks of bacterial diseases and opportunistic infections

High temperature can increase bacterial disease risk in crab culture not simply by favoring a single pathogen, but by simultaneously weakening host defenses and changing the surrounding microbial environment. In aquaculture systems more broadly, elevated water temperatures reduce immunocompetency and increase disease susceptibility, while also increasing loads of opportunistic *Vibrionaceae* in the water column (Samsing and Barnes, 2024). This pattern is relevant to swimming crab because *Vibrio alginolyticus* is already recognized as a major causative agent of emulsification disease associated with large mortality in *P. trituberculatus*.

The infection hazard is amplified during periods when host barriers or physiological stability are compromised. During molting and immediately after molting, swimming crabs are especially vulnerable because the hard carapace and cuticle, which normally act as the first physical barrier against pathogen invasion, are temporarily weakened (Liu et al., 2022). More generally, opportunistic bacterial disease in aquaculture is increasingly understood as a multicausal process driven by environmental stress, host damage, and microbial shifts rather than a simple one-pathogen-one-disease model, which makes high-temperature episodes particularly dangerous under intensive farming conditions (Samsing and Barnes, 2024) (Figure 1).

Mechanisms by Which Elevated Temperature Increases Bacterial Disease Risk in Swimming Crabs

A Multi-factorial Pathway Involving Environment, Host and Microbiome

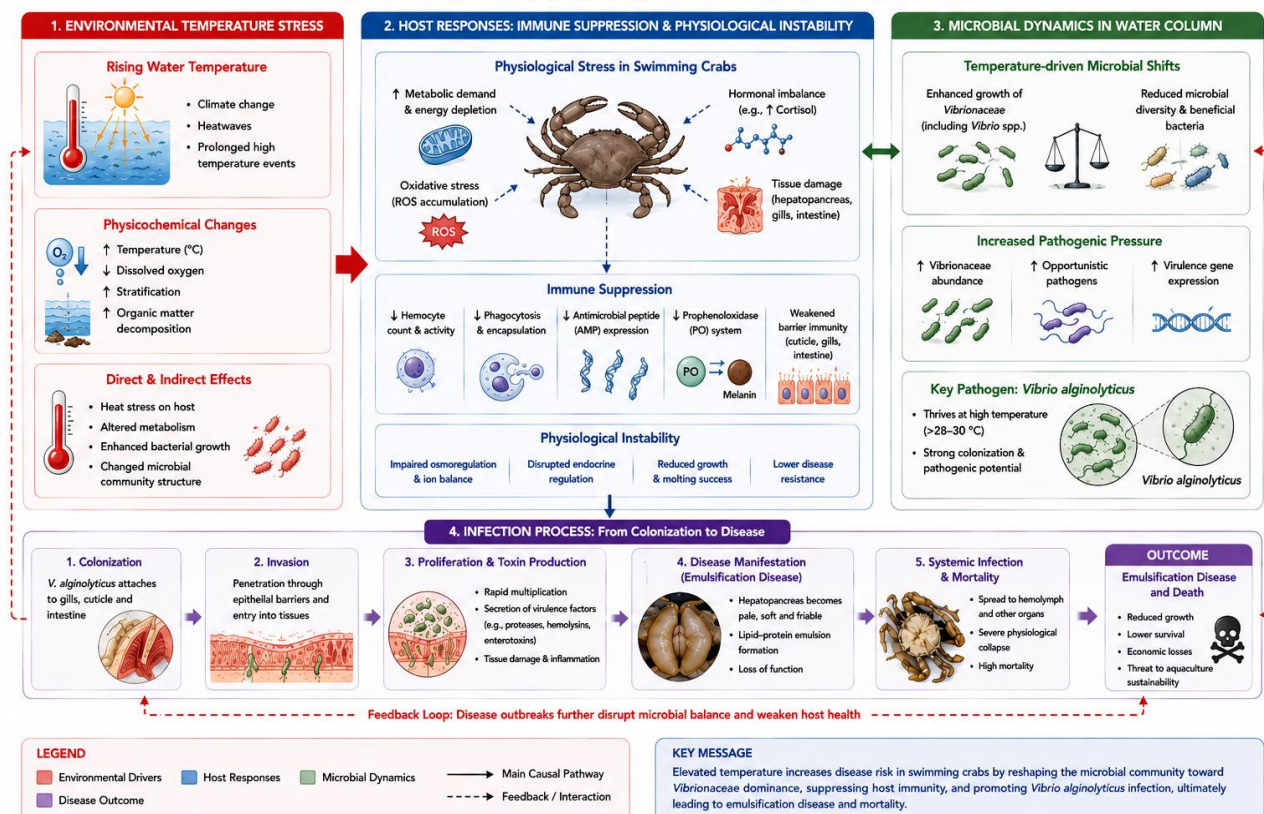


Figure 1 Mechanistic pathway linking high temperature to increased bacterial disease risk in swimming crab (*Portunus trituberculatus*) through host-microbiome interactions

4.3 Molting abnormalities and growth retardation

High temperature can disrupt molting rhythm in swimming crab, and the effect appears to depend on whether temperature remains within a favorable physiological window or exceeds it. Moderate warming often shortens

intermolt periods and accelerates growth, but excessive heat becomes inhibitory: in crablets, 30°C improved molting frequency, growth, and feeding, whereas 34°C significantly reduced ecdysis frequency and slowed growth (Macario et al., 2025). A similar threshold pattern is evident during embryogenesis, where development remained normal at 27°C-29°C, but 31°C-33°C caused asynchronous development, diapause, increased mortality, and sharply reduced hatching success (He et al., 2022).

Current molecular evidence indicates that temperature affects molting through endocrine and metabolic regulation rather than through growth alone. In *P. trituberculatus*, silencing either TRPA1 paralog significantly prolonged the molting interval, and abnormal temperatures altered molting timing through changes in endocrine regulators and metabolic enzymes (Qian et al., 2025). Because successful molting also depends on intact molt signaling and adequate nutritional support, any heat-induced disruption of endocrine coordination is likely to interact with other culture stressors; consistent with this, cholesterol nutrition promotes ecdysone signaling, molting rate, and growth, indicating that growth retardation under heat stress is closely tied to impaired molting physiology rather than to reduced size gain alone (Zhu et al., 2022).

5 Key Health Management Techniques

5.1 Water quality regulation and farming environment optimization techniques

Under high-temperature conditions, water quality regulation should prioritize the stabilization of temperature, dissolved oxygen, pH, and ammonia, because rapid fluctuation in these parameters increases mortality risk and disease susceptibility in aquaculture systems. In swimming crab culture, prolonged summer deterioration of seawater quality can lengthen water-exchange intervals and expose crabs to sustained ammonia stress, while broader aquaculture evidence shows that instability in dissolved oxygen, pH, and temperature directly elevates the risk of production loss. (Lu et al., 2022; Flores-Iwasaki et al., 2025). Ammonia control and ecological optimization are especially important in intensive ponds during hot periods. In *Portunus trituberculatus*, long-term ammonia exposure above 15 mg/L for 15 days severely damages the hepatopancreas and compromises cellular stress responses, indicating that high-temperature management must include measures that reduce organic loading and improve nitrogen processing. Integrated pond regulation can help: nutrient-dynamics modeling showed that residual feed released 41.43% of total feed-derived carbon to the water, while adding razor clams at an appropriate density improved comprehensive water quality in swimming crab-shrimp systems (Lu et al., 2022; Yao et al., 2025).

5.2 Nutritional fortification and immune enhancement strategies

High temperature disrupts nutrient metabolism, increases oxidative stress, and suppresses immune function in crabs, so dietary fortification should focus on antioxidant and immunomodulatory additives. Evidence from chronic heat-stress experiments in crabs shows that elevated temperature increases reactive-oxygen-species-related damage and depresses survival, whereas nutritional intervention can partly restore antioxidant defenses and immune performance (Liu et al., 2023; Wang et al., 2024). Among the tested additives, yeast culture and targeted amino acid or vitamin supplementation appear especially promising for heat-stress mitigation. In juvenile Chinese mitten crab, 3.2 g/kg yeast culture improved survival, antioxidant enzyme activity, immune indices, and gut integrity under chronic heat stress, while high dietary methionine improved survival and reduced oxidative stress and apoptosis at 30°C; similarly, vitamin C at about 133.94-144.81 mg/kg enhanced nonspecific immunity and antioxidant capacity in mud crab. These findings support the use of fortified diets to maintain physiological resilience in swimming crab farming during hot seasons, although direct validation in *P. trituberculatus* under pond heat stress is still limited (Wang et al., 2024).

5.3 Intelligent monitoring and precision farming management techniques

Intelligent monitoring is increasingly central to high-temperature aquaculture management because manual sampling cannot detect sudden changes in temperature, dissolved oxygen, pH, and ammonia quickly enough for timely intervention. Reviews of aquaculture IoT systems show that real-time sensor networks improve growth, reduce mortality, and enable rapid detection of atypical water-quality conditions, while low-cost monitoring platforms can provide continuous parameter tracking with reduced labor input (Shete et al., 2024; Flores-Iwasaki et

al., 2025). For swimming crab culture under thermal stress, the practical value of precision management lies in linking real-time sensing with threshold-based control and predictive intervention. Recent aquaculture studies report that automated systems can trigger oxygenation and pH adjustment during warm periods, maintaining survival above 90%, and sensor architectures can be adapted to control temperature, pH, and ammonia through pumps or heaters once preset thresholds are exceeded. Therefore, intelligent farming for swimming crab should integrate continuous sensing, early-warning models, and automated response functions to reduce the lag between environmental deterioration and management action (Zein et al., 2023; Baena-Navarro et al., 2025).

6 Case Study: Health Management Practices for Swimming Crab During High-Temperature Seasons

6.1 Overview of the case study farming area and high-temperature characteristics

The case study area can be characterized as a semi-closed coastal pond farming system for *Portunus trituberculatus* operating under intensive or polyculture conditions, where water exchange is relatively limited and environmental regulation depends strongly on in-pond management. In a representative integrated pond in Zhoushan, Zhejiang, the culture area was 1.33 ha with an average water depth of 1.2 m, salinity ranged from 14.5 to 19.0, and water exchange occurred only 1-2 times per month, which is consistent with management conditions that can magnify summer water-quality stress (Dong et al., 2022). Microbial evidence from semi-closed polyculture ponds likewise shows lower α -diversity under limited water exchange, indicating that enclosed high-temperature culture areas are ecologically sensitive and require close environmental control (Huang et al., 2024).

High-temperature exposure in such farming areas is both seasonal and biologically consequential. In early autumn culture, pond water is commonly around 30°C and can occasionally reach 33°C, while experimental evidence indicates that embryonic development remains relatively normal below 31°C but deteriorates above that threshold, with increased mortality and reduced hatching at 31°C-33°C (He et al., 2022). Elevated temperature also alters behavior and production risk in juvenile or adult crabs, because 30°C significantly increased aggressiveness and reduced behavioral predictability, while chronic summer heat in crab aquaculture more broadly is associated with oxidative stress, immune disturbance, and greater disease pressure (Liu et al., 2023).

6.2 Implementation process of health management measures

The implementation of health management during high-temperature seasons should begin with continuous water-quality regulation, especially for temperature, dissolved oxygen, pH, and ammonia. Real-time aquaculture monitoring studies show that IoT-based systems can continuously track these parameters and support rapid intervention when conditions deviate from preset thresholds, while broader sensor reviews indicate that such systems reduce mortality risk and improve the detection of atypical total ammonia nitrogen events (Shete et al., 2024; Flores-Iwasaki et al., 2025). For swimming crab ponds, this monitoring should be paired with restrained feeding, timely removal of residual feed, and controlled water exchange, because nutrient-dynamics simulations show major nutrient release from uneaten feed and summer seawater deterioration can prolong exchange intervals and intensify ammonia exposure (Dong et al., 2022; Lu et al., 2022).

A second part of the implementation process is ecological and biological stress reduction. Appropriate integrated culture can be used to improve the pond environment, because adding razor clams at suitable density improved water quality indices in swimming crab-shrimp systems, while microbial studies in swimming crab ponds suggest that potential pathogens such as *Vibrio*, *Photobacterium*, and *Flavobacterium* deserve focused surveillance during culture (Huang et al., 2024; Yao et al., 2025). At the animal level, stress buffering can be strengthened through environmental and nutritional measures: sand or PVC enrichment improved survival and reduced stress responses in *P. trituberculatus*, and heat-stress studies in crabs show that dietary supplementation such as yeast culture can improve survival, antioxidant status, immune performance, and gut health under prolonged thermal load (Xiong et al., 2024; Wang et al., 2024).

6.3 Evaluation of application effects and summary of experiences

The application effects of these measures can be evaluated from the perspectives of water stability, physiological protection, and production performance. Ammonia management is especially important, because environmentally relevant ammonia exposure suppresses energy metabolism, increases oxidative damage, and impairs reproduction in the hepatopancreas of female swimming crab, while long-term exposure above 15 mg/L for 15 days causes severe hepatopancreatic damage and depressed cellular stress responses (Meng et al., 2021; Lu et al., 2022). These findings indicate that health management is effective when it prevents the combined rise of temperature and ammonia rather than treating them as separate hazards.

Experience from related aquaculture systems suggests that integrated monitoring and timely correction can produce clear management benefits, but outcomes still depend on keeping heat exposure within the species' physiological tolerance window. Predictive IoT-ML systems in tropical ponds maintained survival above 90% through continuous monitoring and repeated corrective interventions, and postharvest temperature-control studies in swimming crab products similarly show that low-temperature handling suppresses microbial growth and quality deterioration (Chen et al., 2023; Baena-Navarro et al., 2025). Overall, the main practical lessons are to monitor key water variables continuously, reduce organic and ammonia loading before stress accumulates, combine ecological regulation with animal-level stress mitigation, and respond early once pond temperature approaches 30°C-31°C, because risk rises sharply beyond that range (He et al., 2022; Lu et al., 2025) (Figure 2).

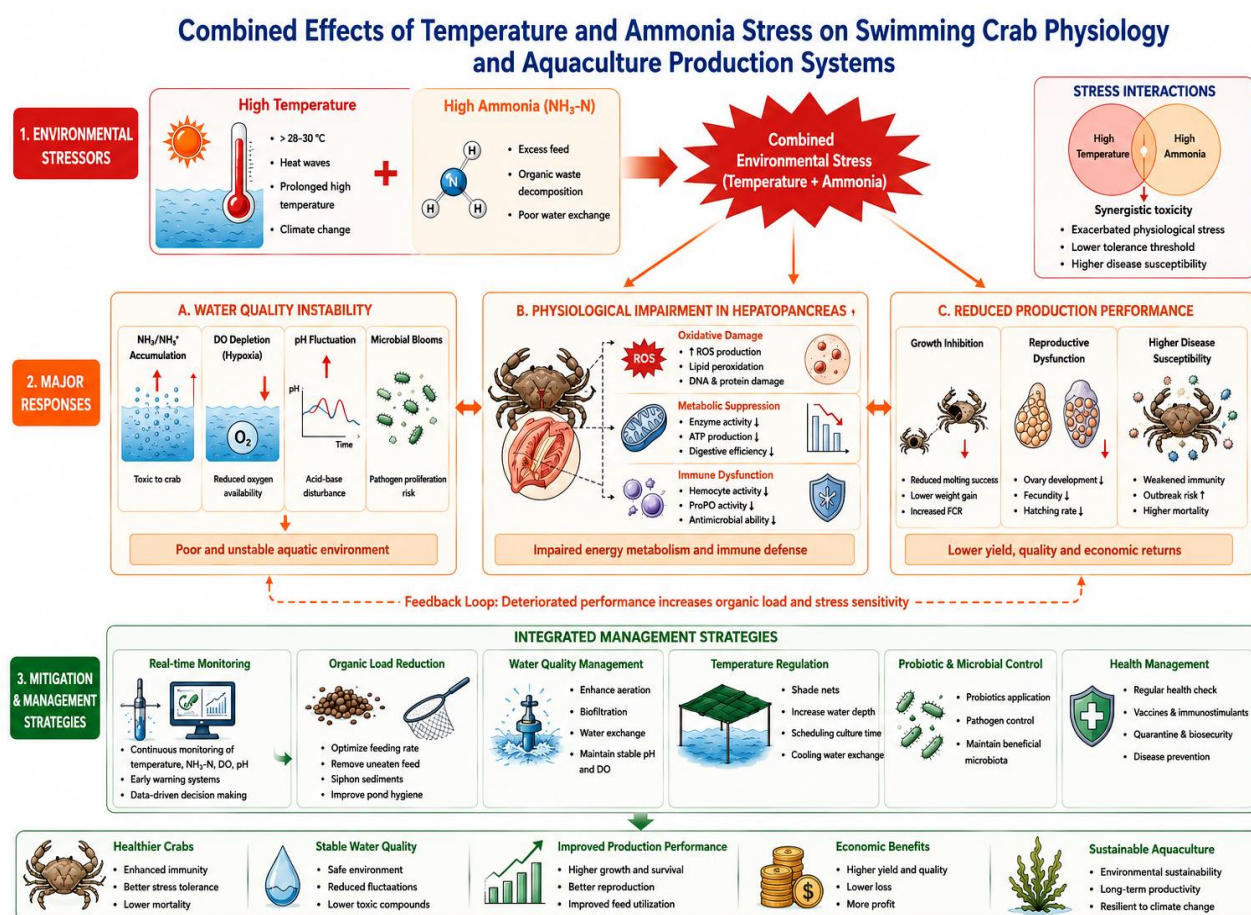


Figure 2 Environmental threshold levels and associated physiological risks in swimming crab aquaculture

7 Challenges in Health Management Under High Temperature

7.1 Management pressures arising from frequent extreme high-temperature events

Frequent extreme high-temperature events intensify the difficulty of maintaining the physiological stability of swimming crab culture systems because temperature directly affects crustacean metabolism, growth, moulting,

immunity, and survival, while climate warming is increasing the frequency of damaging thermal exposure in aquaculture environments (Qian et al., 2024; Daunde et al., 2025). For swimming crab specifically, high temperature can disrupt energy metabolism, and severe stress is especially likely when elevated temperature is combined with air exposure, indicating that routine operations such as handling, grading, and transport become riskier during hot periods.

Extreme heat also creates management pressure by pushing crabs toward ecological and physiological thresholds beyond which recovery becomes difficult. In a related portunid crab fishery, juveniles became most susceptible when summer temperatures exceeded 24°C and conditions became clearly detrimental above 26°C, showing how short periods of abnormal warming can impair recruitment and survival. At the behavioral level, elevated temperature increases aggressiveness in *Portunus trituberculatus*, which can aggravate interference, injury, and cannibalism risk under high-density farming conditions (He et al., 2025).

7.2 Limitations in health monitoring and disease early-warning technologies

A major challenge under high-temperature conditions is that health deterioration often develops before farmers can identify it with conventional farm surveillance. Aquatic animal disease diagnostics still rely heavily on visual observation and traditional laboratory methods, while rapid kits and field-deployable tools remain insufficiently mature for routine farm use. Although CRISPR-, biosensor-, and LAMP-based tools are being developed, current field applications still face limitations in sensitivity and specificity, reducing their reliability for early warning during fast-moving heat-associated disease events (Bohara et al., 2023).

The second limitation is that effective early warning under heat stress requires integrated environmental forecasting, yet such systems remain uncommon in aquaculture practice. Temperature-sensitive marine diseases can be monitored using surveillance tools based on environmental temperature outlooks, and these tools can help target monitoring and management actions. However, outbreak risk is driven by nonlinear interactions among temperature, salinity, oxygen, pH, and host-pathogen factors, which makes prediction difficult for traditional approaches even though newer machine-learning systems show promise (Xie et al., 2025).

7.3 Lag in the development of integrated management systems and standardization

Integrated management systems for coping with high temperature in swimming crab farming still lag behind the needs of increasingly intensive production. Intensification raises stress through crowding, waste accumulation, and water-quality deterioration, and successful high-density culture depends on continuous balancing of biological and environmental variables that many farms still cannot achieve consistently (Emerenciano et al., 2022). This means that heat management cannot be treated as a single-factor issue, because elevated temperature interacts with oxygen, water quality, stocking density, and biosecurity failures to amplify health risks (Hapsari et al., 2025).

Standardization also remains limited because existing intelligent and integrated systems are still fragmented, species-specific, or insufficiently translated into broadly applicable farm protocols. Recent intelligent aquaculture systems can dynamically regulate temperature and oxygen using real-time stress feedback and can reduce chronic stress or disease incidence while improving operational performance, but these results mostly come from experimental systems in fish or shrimp rather than standardized frameworks for swimming crab culture (Nie et al., 2025). Likewise, integrated multi-trophic models such as shrimp-crab polyculture improve resource use and water-quality management potential, yet adoption depends strongly on local conditions, indicating that unified standards for high-temperature health management remain underdeveloped (Chang et al., 2020).

8 Conclusions and Future Perspectives

Current research shows that high temperature disrupts health homeostasis in *Portunus trituberculatus* at multiple levels, including energy metabolism, behavior, and cellular protection. Elevated temperature increases lactate accumulation, depresses ATP-related energy status, and can create a mismatch between energy demand and supply, especially when crabs are also exposed to air, which helps explain stress-induced mortality during culture and handling. In parallel, temperature elevation intensifies agonistic interactions and cannibalism risk, with fighting

frequency and duration rising as temperature increases, indicating that thermal stress management must include both physiological and behavioral regulation.

Mechanistic work has further expanded this framework from phenotype to molecular regulation. Multi-omics evidence indicates that warming enhances aggressiveness through coordinated activation of energy metabolism and neural signaling pathways, while recent gene-level studies suggest that temperature perception in swimming crab involves broad induction of transient receptor potential channel genes under acute thermal stress. Together, these advances show that high-temperature health management is no longer limited to maintaining survival, but increasingly targets early stress recognition, metabolic stabilization, and the reduction of secondary risks such as injury, hypoxia, and immune imbalance.

The next stage of technology development should prioritize real-time, data-driven monitoring systems that can detect environmental deterioration and disease risk before mass losses occur. Recent aquaculture studies show that integrated IoT platforms can continuously track key variables such as pH, dissolved oxygen, and redox conditions, while machine-learning models can convert these data into disease prediction and automated warning outputs for farm management. More broadly, intelligent aquaculture frameworks that combine sensors, big-data processing, and AI-based decision systems appear well suited for swimming crab farming under heat stress, because they can shift management from experience-based reaction to evidence-based prevention.

A second development direction is rapid and field-deployable health diagnostics linked with stress biomarkers and epidemiological forecasting. Emerging aquamedicine tools, including biosensors, sequencing, CRISPR-based assays, drones, and AI-assisted monitoring, have already improved the speed of pathogen detection and farm surveillance, but broader adoption still requires lower-cost kits and better farmer training. In parallel, predictive systems that integrate surveillance with environmental drivers are becoming increasingly feasible; machine learning models using real-time or near-real-time environmental data now provide scalable outbreak forecasting frameworks that could be adapted to swimming crab pathogens under high-temperature conditions.

In the context of climate change, sustainable swimming crab aquaculture will depend on combining farm-level health management with broader adaptation planning. Reviews across aquaculture systems show that rising temperature alters physiology, feeding, immunity, and disease dynamics, while prolonged warming increasingly threatens productivity and sustainability, making adaptation an immediate rather than future requirement. For crustacean farming specifically, resilience pathways increasingly center on selective breeding, species or system diversification, dietary intervention, and technological upgrading, because thermal sensitivity affects growth, moulting, immune response, and survival across cultured taxa.

Long-term sustainability also requires climate-resilient production models supported by governance, forecasting, and ecological safeguards. Recirculating or integrated systems, environmental control strategies, and planned adaptation measures can reduce exposure to climate stressors, but their success depends on timely environmental information, regional planning, and policy support rather than farm-level action alone. At the same time, future development should avoid a narrow focus on productivity, because intelligent and genetic technologies can create ecological or animal-health tradeoffs if they are applied without localization, biodiversity protection, and sustainability oversight.

Reference

- Baena-Navarro R., Carriazo-Regino Y., Torres-Hoyos F., and Pinedo-López J., 2025, Intelligent prediction and continuous monitoring of water quality in aquaculture: integration of machine learning and Internet of Things for sustainable management, *Water*, 17(1): 82.
<https://doi.org/10.3390/w17010082>
- Bohara K., Joshi P., Acharya K., and Ramena G., 2023, Emerging technologies revolutionising disease diagnosis and monitoring in aquatic animal health, *Reviews in Aquaculture*, 16(2): 836-854.
<https://doi.org/10.1111/raq.12870>
- Chang Z., Neori A., He Y., Li J., Qiao L., Preston S., Liu P., and Li J., 2020, Development and current state of seawater shrimp farming, with an emphasis on integrated multi-trophic pond aquaculture farms, in China - a review, *Reviews in Aquaculture*, 12(4): 2544-2558.
<https://doi.org/10.1111/raq.12457>

- Chen Y., Li P., Xu D., Zhang X., and Huang T., 2023, Quality and microbiome analysis of pickled swimming crabs (*Portunus trituberculatus*) during storage at two alternative temperatures, *Molecules*, 28(23): 7744.
<https://doi.org/10.3390/molecules28237744>
- Coates C.J., and Söderhäll K., 2020, The stress-immunity axis in shellfish, *Journal of Invertebrate Pathology*, 186: 107492.
<https://doi.org/10.1016/j.jip.2020.107492>
- Daunde V.V.Y., Kamble M., Chavan B.R., Palekar G.K.R., Tayade S.H., Ponpompisit A., Thompson K.D., Medhe S.V., and Pirarat N., 2025, Effects of climate change-induced temperature rise on crustacean aquaculture: a comprehensive review, *Aquaculture and Fisheries*, 10(4): 100-118.
<https://doi.org/10.1016/j.aaf.2025.08.008>
- Dong S., Xu X., Lin F., Yu L., Shan H., and Wang F., 2022, A discontinuous individual growth model of swimming crab *Portunus trituberculatus* and its application in the nutrient dynamic simulation in an intensive mariculture pond, *Frontiers in Marine Science*, 9: 918449.
<https://doi.org/10.3389/fmars.2022.918449>
- Emerenciano M., Rombenso A., Vieira F.N., Martins M.A., Coman G., Truong H., Noble T., and Simon C., 2022, Intensification of penaeid shrimp culture: an applied review of advances in production systems, nutrition and breeding, *Animals*, 12(3): 236.
<https://doi.org/10.3390/ani12030236>
- Flores-Iwasaki M., Guadalupe G.A., Pachas-Caycho M., Chapa-Gonza S., Mori-Zabarburú R.C., and Guerrero-Abad J., 2025, Internet of Things (IoT) sensors for water quality monitoring in aquaculture systems: a systematic review and bibliometric analysis, *AgriEngineering*, 7(3): 78.
<https://doi.org/10.3390/agriengineering7030078>
- Hapsari F., Suprayudi M.A., Akiyama D.M., Ekasari J., Norouzitallab P., and Baruah K., 2025, Decoding stress responses in farmed crustaceans: comparative insights for sustainable aquaculture management, *Biology*, 14(8): 920.
<https://doi.org/10.3390/biology14080920>
- He J., Wan L., Yu H., Peng Y., Zhang D., and Xu W., 2022, Effect of water temperature on embryonic development of *Portunus trituberculatus* in an off-season breeding mode, *Frontiers in Marine Science*, 9: 1066151.
<https://doi.org/10.3389/fmars.2022.1066151>
- He K., Liang Q., Liu D., and Wang F., 2025, Elevated temperature enhances aggressiveness in the swimming crab (*Portunus trituberculatus*): a study integrating behavior and multi-omics, *Marine Pollution Bulletin*, 223: 119038.
<https://doi.org/10.1016/j.marpolbul.2025.119038>
- Huang Q., Li M., Xu S., and Li C., 2024, Temporal dynamics of microbial communities in the water of polyculture pond system for Chinese swimming crab *Portunus trituberculatus*, *Journal of Experimental Marine Biology and Ecology*, 579: 152047.
<https://doi.org/10.1016/j.jembe.2024.152047>
- Jiang Y., Liu X., Shang Y., Li J., Gao B., Ren Y., and Meng X., 2024, Physiological and transcriptomic analyses provide insights into nitrite stress responses of the swimming crab *Portunus trituberculatus*, *Marine Biotechnology*, 26(5): 1040-1052.
<https://doi.org/10.1007/s10126-024-10353-5>
- Kumar P.V., Roy S., Behera B., and Das B., 2022, Heat shock proteins (Hsps) in cellular homeostasis: a promising tool for health management in crustacean aquaculture, *Life*, 12(11): 1777.
<https://doi.org/10.3390/life12111777>
- Li Z., Zhao Z., Luo L., Wang S., Zhang R., Guo K., and Yang Y., 2022, Immune and intestinal microbiota responses to heat stress in Chinese mitten crab (*Eriocheir sinensis*), *Aquaculture*, 563: 738965.
<https://doi.org/10.1016/j.aquaculture.2022.738965>
- Lin W.-J., Ren Z., Mu C., Ye Y., and Wang C., 2020, Effects of elevated pCO₂ on the survival and growth of *Portunus trituberculatus*, *Frontiers in Physiology*, 11: 750.
<https://doi.org/10.3389/fphys.2020.00750>
- Liu J., Zhang C., Wang X., Li X., Huang Q., Wang H., Miao Y., Li E., Qin J., and Chen L., 2023, Dietary methionine level impacts the growth, nutrient metabolism, antioxidant capacity and immunity of the Chinese mitten crab (*Eriocheir sinensis*) under chronic heat stress, *Antioxidants*, 12(1): 209.
<https://doi.org/10.3390/antiox12010209>
- Liu M., Ni H., Zhang X., Sun Q., Wu X., and He J., 2022, Comparative transcriptomics reveals the immune dynamics during the molting cycle of swimming crab *Portunus trituberculatus*, *Frontiers in Immunology*, 13: 1037739.
<https://doi.org/10.3389/fimmu.2022.1037739>
- Lu Y., Liu Y., Cao J., Zhang Y., Zheng Y., and Wang F., 2025, Waterborne ammonia toxicity damages crustacean hemocytes via lysosome-dependent autophagy: a case study of swimming crabs *Portunus trituberculatus*, *Environmental Research*, 272: 120985.
<https://doi.org/10.1016/j.envres.2025.120985>
- Lu Y., Zhang J., Cao J., Liu P., Li J., and Meng X., 2022, Long-term ammonia toxicity in the hepatopancreas of swimming crab *Portunus trituberculatus*: cellular stress response and tissue damage, *Frontiers in Marine Science*, 8: 757602.
<https://doi.org/10.3389/fmars.2021.757602>
- Lu Y., Zhu B., Zhang D., and Li Y., 2020, Air temperature and emersion time can affect the survival rate and ammonium loading of swimming crab *Portunus trituberculatus* exposed to air, *Journal of Ocean University of China*, 19(3): 643-652.
<https://doi.org/10.1007/s11802-020-4154-5>

- Macario A.C., Islam T., Paz M., Balsomo A.J., and Tomiyama T., 2025, Temperature-induced effects on ecdysis frequency, feeding, and growth response of gazami (*Portunus trituberculatus*) crablets, *Aquaculture, Fish and Fisheries*, 5(6): e70141.
<https://doi.org/10.1002/aff2.70141>
- Meng X., Jayasundara N., Zhang J., Ren X., Gao B., Li J., and Liu P., 2021, Integrated physiological, transcriptome and metabolome analyses of the hepatopancreas of the female swimming crab *Portunus trituberculatus* under ammonia exposure, *Ecotoxicology and Environmental Safety*, 228: 113026.
<https://doi.org/10.1016/j.ecoenv.2021.113026>
- Mugwanya M., Dawood M., Kimera F., and Sewilam H., 2022, Anthropogenic temperature fluctuations and their effect on aquaculture: a comprehensive review, *Aquaculture and Fisheries*, 7(3): 223-243.
<https://doi.org/10.1016/j.aaf.2021.12.005>
- Nie Y., Yang H., Qu K., Zhang L., and Du J., 2025, Research on the development and application of an intelligent aquaculture system, *Information Resources Management Journal*, 38(1): 1-20.
<https://doi.org/10.4018/irmj.368721>
- Qian Y., Yu Q., Zhang J., Han Y., Xie X., and Zhu D., 2024, Identification of transient receptor potential channel genes from the swimming crab *Portunus trituberculatus* and their expression profiles under acute temperature stress, *BMC Genomics*, 25(1): 72.
<https://doi.org/10.1186/s12864-024-09973-x>
- Qian Y., Yu Q., Zhang J., Han Y., Xie X., and Zhu D., 2025, Molecular characterization of TRPA1 and its function in thermotaxis and molting in *Portunus trituberculatus*, *Aquaculture Reports*, 45: 103158.
<https://doi.org/10.1016/j.aqrep.2025.103158>
- Qiu L., Guo X., Xie G., Feng Y.-H., Xing J.-Y., Li C., Yang B., and Huang J., 2023, Description of a natural infection with decapod iridescent virus 1 in farmed swimming crab, *Aquaculture*, 574: 739681.
<https://doi.org/10.1016/j.aquaculture.2023.739681>
- Samsing F., and Barnes A.C., 2024, The rise of the opportunists: what are the drivers of the increase in infectious diseases caused by environmental and commensal bacteria?, *Reviews in Aquaculture*, 16(4): 1787-1797.
<https://doi.org/10.1111/raq.12922>
- Shete R.P., Bongale A.M., and Dharrao D., 2024, IoT-enabled effective real-time water quality monitoring method for aquaculture, *MethodsX*, 13: 102906.
<https://doi.org/10.1016/j.mex.2024.102906>
- Su X., Liu J., Wang F., Wang Q., Zhang D., Zhu B., and Liu D., 2020, Effect of temperature on agonistic behavior and energy metabolism of the swimming crab *Portunus trituberculatus*, *Aquaculture*, 516: 734573.
<https://doi.org/10.1016/j.aquaculture.2019.734573>
- Wang B., Yang H., Mao H., and Shi Q., 2025, Development and testing of an aquaculture environmental control system based on behavioral stress responses, *Life*, 15(12): 1809.
<https://doi.org/10.3390/life15121809>
- Wang S., Li E., Luo Z., Li X., Liu Z., Li W., Wang X., Qin J., and Chen L., 2024, Dietary yeast culture can protect against chronic heat stress by improving survival, antioxidant capacity, immune response, and gut health of juvenile Chinese mitten crab (*Eriocheir sinensis*), *Aquaculture*, 596: 741910.
<https://doi.org/10.1016/j.aquaculture.2024.741910>
- Wu J., Wan L., Li B., Zhang D., Shi H., Zhang T., Ping H., and He J., 2024, Effect of water temperature on the development of *Portunus trituberculatus* larvae in off-season breeding mode, *Crustaceana*, 97(3-4): 201-220.
<https://doi.org/10.1163/15685403-bja10350>
- Xie X., Zhang B., Wang X., Jiang Y., Buchmann K., Zhou S., Li Y., Yin F., and Galindo-Villegas J., 2025, A machine learning-driven early warning system for cryptocaryoniasis in marine aquaculture, *Parasites and Vectors*, 18(1): 490.
<https://doi.org/10.1186/s13071-025-07124-z>
- Xiong T., Mu C., Wang C., Sun P., He J., Shi C., and Ye Y., 2024, Environmental enrichment improves survival and growth of *Portunus trituberculatus* in recirculating aquaculture system by reducing energy expenditure and stress responses, *Aquaculture*, 584: 740544.
<https://doi.org/10.1016/j.aquaculture.2024.740544>
- Yao S., Liu H., Zhang D., Chen Y., Li S., He J., and Xu W., 2025, The potential influence of clams on water quality improvement in mariculture ponds: a comprehensive assessment utilizing single-factor and water quality index methods, *Aquaculture International*, 33(2): 143.
<https://doi.org/10.1007/s10499-025-01829-9>
- Yin L., Fu L., Wu H., Xia Q., Jiang Y., Tan J., and Guo Y., 2021, Modeling dissolved oxygen in a crab pond, *Ecological Modelling*, 440: 109385.
<https://doi.org/10.1016/j.ecolmodel.2020.109385>
- Zein M.I., Mujiyanti I.S.F., Pratama I.P.E.W., Darmawan T.R., and Lokswara R., 2023, Monitoring and control system for pH and temperature of water quality on the vertical mud crab cultivation, *Proceedings of the 2023 International Conference on Advanced Mechatronics, Intelligent Manufacture and Industrial Automation (ICAMIMIA)*, 2023: 1-6.
<https://doi.org/10.1109/icamimia60881.2023.10427614>
- Zhan W., Peng H., Xie S., Deng Y., Zhu T., Cui Y., Cao H., Tang Z., Jin M., and Zhou Q.-C., 2024, Dietary lauric acid promoted antioxidant and immune capacity by improving intestinal structure and microbial population of swimming crab (*Portunus trituberculatus*), *Fish and Shellfish Immunology*, 151: 109739.
<https://doi.org/10.1016/j.fsi.2024.109739>

- Zhu B., Liu D., and Wang F., 2026, Interactions between crabs and the environment: progress and prospects from a behavioral perspective, *Reviews in Aquaculture*, 18(1): e70122.
<https://doi.org/10.1111/raq.70122>
- Zhu T., Zhou Q.-C., Yang Z., Zhang Y., Luo J., Zhang X., Shen Y., Jiao L., Tocher D.R., and Jin M., 2022, Dietary cholesterol promotes growth and ecdysone signalling pathway by modulating cholesterol transport in swimming crabs (*Portunus trituberculatus*), *Animal Nutrition*, 10(1): 249-260.



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Feature Review

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Water Quality Control and Fish Health Management in Recirculating Aquaculture Systems

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Abstract Recirculating aquaculture systems (RAS) have emerged as an important technology for sustainable aquaculture development due to their advantages in water conservation, environmental control, and high-density fish production. However, maintaining optimal water quality and preventing fish health problems remain major challenges in intensive RAS operations. This review focuses on the relationship between water quality control and fish health management in recirculating aquaculture systems. The fundamental mechanisms regulating water quality are first discussed, including the dynamics of dissolved oxygen, temperature, pH, ammonia, nitrite, nitrate, carbon dioxide, and microbial communities. The impacts of water quality fluctuations on fish physiological responses, growth performance, immune function, and disease susceptibility are further analyzed. Subsequently, advances in monitoring technologies, including sensor networks, Internet of Things (IoT) platforms, and data-driven approaches, are summarized for real-time environmental assessment and management. Strategies for maintaining stable water conditions, such as mechanical filtration, biological treatment, oxygen regulation, nutrient management, and microbial regulation, are evaluated. A case study framework is presented to demonstrate the integration of water quality monitoring, fish health assessment, and intelligent management strategies in commercial RAS facilities. Furthermore, the potential applications of artificial intelligence, predictive modeling, and automated control systems are discussed. Future research should focus on multi-source data integration, intelligent decision-support systems, and sustainable management technologies to improve production efficiency, fish welfare, and environmental sustainability in recirculating aquaculture.

Keywords Recirculating aquaculture systems; Water quality control; Fish health management; Intelligent aquaculture; Biofiltration technology

1 Introduction

Recirculating aquaculture systems (RAS) have emerged as a major technological pathway for intensifying aquaculture while reducing its dependence on large volumes of water and limiting effluent release. Their development has accelerated because RAS can operate in controlled indoor environments, recycle most of the culture water, improve biosecurity, and support more predictable production under environmental and climate-related constraints (Gupta et al., 2024). Earlier and more recent reviews alike describe RAS as high-control, high-reuse production systems whose core value lies in decoupling fish farming from local water availability while improving waste management and nutrient recycling. At the same time, the importance of RAS is not only environmental but strategic: these systems are increasingly viewed as a means to expand aquaculture production with lower ecological impact, stronger containment of escapees and pathogens, and greater resilience to drought, salinity shifts, and other external stressors that threaten open systems (Ahmed and Turchini, 2021). This combination of production control and environmental performance has made RAS central to discussions of sustainable aquaculture, even though energy demand, capital cost, and managerial complexity still constrain broader adoption.

The advantages of RAS, however, depend on maintaining water quality within narrow and species-specific limits, because fish in intensive recirculating environments are continuously exposed to the same water matrix and to the consequences of any treatment failure. Water quality in RAS includes physical, chemical, and biological dimensions, and the key variables routinely monitored include temperature, dissolved oxygen, pH, salinity, oxidation-reduction potential, turbidity, and suspended solids, all of which shape fish growth, stress, and disease risk (Dai et al., 2025).

Pollutants generated by feed inputs and fish excretion, particularly particulate matter, ammonia, nitrite, nitrate, carbon dioxide, and microbial loads, can accumulate in recirculating loops and impair both system performance and animal health if removal processes are insufficient (Li et al., 2023). Reviews focused on fish welfare in RAS further emphasize that degraded water quality affects not only survival and feed conversion but also gill integrity, immune responses, and behavior, making water quality a direct determinant of fish health rather than a background husbandry variable (Holan et al., 2020; Bjørgen et al., 2024). This relationship is especially important in high-density production, where organic loading, bacterial growth, and fluctuating oxygen conditions can propagate rapidly through the system and magnify subclinical stress into health and welfare problems (Lindholm-Lehto, 2023).

Research in recent years has therefore shifted from describing individual water quality variables toward integrated water quality-based fish health management. Current work highlights the need for rapid, real-time, and automated monitoring technologies, including IoT-linked sensors, online measurement platforms, and behavior-based surveillance tools that can detect emerging deterioration before overt disease or mortality occurs (Lindholm-Lehto, 2023). This shift is reinforced by disease-management studies showing that effective fish health protection depends on preventive surveillance, quality health data, and early warning rather than treatment after outbreaks, especially because conventional chemotherapy can disrupt biofilters and destabilize water quality in RAS (Holan et al., 2020). Parallel advances in predictive analytics have extended this approach by using machine learning and knowledge-based systems to identify water quality degradation, diagnose disease risks, and support decision-making before losses become severe (Islam et al., 2024). Together, these developments show that fish health management in RAS is increasingly becoming a data-centric discipline in which water quality control, system monitoring, and biosecurity are operationally inseparable (Gupta et al., 2024).

Against this background, the objective of water quality-based fish health management is no longer simply to keep individual parameters within acceptable ranges, but to build integrated control frameworks that connect environmental monitoring, treatment performance, fish responses, and management decisions. Recent reviews argue that full control of water quality and optimization of rearing conditions are the main conditions for sustainable RAS operation, while also noting that the field still lacks standardization in what parameters are measured, how often they are measured, and what fluctuations are acceptable across systems and species (Gupta et al., 2024). Important methodological gaps also remain, including incomplete reporting of water quality in fish health studies, inconsistent interpretation of health indicators such as gill responses, and the need for commercial-scale data that can support more reliable and transferable management models (Bjørgen et al., 2024). Accordingly, this paper is grounded in the premise that intelligent water quality control must combine conventional engineering with biological surveillance and predictive modeling to support fish welfare, stable production, and lower environmental cost (Kamali et al., 2022). In that sense, the central research task is to clarify how water quality information can be translated into actionable fish health management strategies for next-generation RAS.

2 Fundamental Mechanisms of Water Quality Regulation in Recirculating Aquaculture Systems

2.1 Dynamics and control of major water quality parameters

Water quality regulation in RAS depends on controlling a tightly coupled set of variables, especially ammonia, nitrite, nitrate, dissolved oxygen, and pH, because these parameters shift continuously with feeding, fish metabolism, biofilter activity, and water exchange (Lindholm-Lehto, 2023). Dynamic modeling shows that parameter stability is not static but emerges from feedback loops linking waste production, oxygen demand, and treatment-unit performance, which is why operational changes in stocking density, feed intensity, or aeration can rapidly alter system water chemistry (Udayakumar et al., 2025).

Among the major parameters, dissolved oxygen, temperature, and pH have especially strong control effects because they influence both fish physiology and the toxicity or transformation of nitrogenous wastes. In RAS, increasing temperature lowers dissolved oxygen availability and increases ammonia toxicity, while extreme pH directly destabilizes other critical parameters; field observations likewise show that pH variability reflects the combined effects of nitrification, carbon dioxide stripping, and buffering, making precise pH control essential for stable operation (Pepe-Victoriano et al., 2025).

2.2 Biological processes maintaining water quality in ras

The core biological mechanism maintaining water quality in RAS is microbial nitrogen conversion within biofilters, where toxic ammonium is oxidized into nitrite and then nitrate, reducing acute toxicity in the culture water (Lindholm-Lehto et al., 2020). This process is now understood as more complex than the classical two-step nitrification model, because coupled nitrogen removal can also involve aerobic denitrifiers, anammox organisms, and comammox microorganisms that together improve total nitrogen removal under low-water-exchange conditions (Preena et al., 2021).

Biological regulation also depends on community structure and engineered enhancement of microbial function rather than on nitrification alone. In recirculating pond systems, bacteria-microalgae associations with biofilm carriers reduced total nitrogen, TAN, and nitrite while increasing functional genes linked to ammonia oxidation and denitrification, and biofloc biofilters similarly concentrated denitrifiers, nitrifiers, and phosphorus-removing microorganisms in the reaction zones where most nutrient removal occurred.

2.3 Effects of water quality fluctuations on fish physiological responses

Water quality fluctuations affect fish first through stress physiology, and dissolved oxygen depletion is one of the most immediate threats in intensive systems. Hypoxia below about 1-2 mg/L for even a few hours can suppress growth and cause mortality, while broader reviews of RAS species responses show that excessively low dissolved oxygen disrupts system balance and produces losses that can quickly become unacceptable under intensive culture conditions (Dai et al., 2025).

Nitrogenous waste accumulation produces a second major physiological pathway of harm because elevated ammonia alters biochemical, physiological, immunological, and homeostatic processes, increasing disease susceptibility. This toxicity is not fixed, since its severity rises or falls with pH, temperature, salinity, dissolved oxygen, species, and life stage, and RAS observations confirm that even when overall water quality remains acceptable, fluctuations such as unstable pH and low alkalinity can still generate measurable fish stress (Pepe-Victoriano et al., 2025).

3 Water Quality Monitoring Technologies and Data Acquisition in RAS

3.1 Conventional methods for water quality assessment

Conventional water quality assessment in RAS has relied mainly on periodic manual sampling, portable meters, and laboratory analysis of key physicochemical variables. These approaches remain foundational because they are used to track core indicators such as pH, temperature, dissolved oxygen, salinity, turbidity, and oxidation-reduction conditions, but they are labor-intensive and provide only intermittent snapshots of system status rather than continuous process awareness (Lindholm-Lehto, 2023). In intensive recirculating systems, that sampling logic is useful for routine compliance and baseline husbandry, yet it is inherently limited when water quality shifts rapidly between observation intervals.

The main weakness of conventional assessment is therefore not analytical validity but delayed detection of critical change. Manual sampling and laboratory workflows are costly in labor and time, do not support immediate intervention, and can miss off-hour excursions in dissolved oxygen, pH, or temperature that affect fish performance before personnel become aware of them (Figure 1) (Flores-Iwasaki et al., 2025). At the same time, RAS water assessment increasingly extends beyond basic field measurements to more specialized analyses, including in situ ion chromatography for continuous nitrite and nitrate monitoring and HPLSEC-fluorescence methods for tracking dissolved organic matter under oxidative treatment conditions.

3.2 Application of sensor networks and IoT technologies

Sensor networks and IoT technologies have shifted RAS monitoring from interval-based observation to real-time acquisition and remote supervision. Current systems integrate sensors for temperature, pH, dissolved oxygen, turbidity, salinity, conductivity, or water level with wireless communication modules and cloud-connected dashboards, allowing farmers to visualize conditions continuously and receive warning signals when thresholds are

exceeded (Malandrakis, 2025). This architecture is especially valuable in RAS because equipment failures or rapid water-quality deterioration can escalate quickly, making immediate alerts and remote access more useful than retrospective records alone.

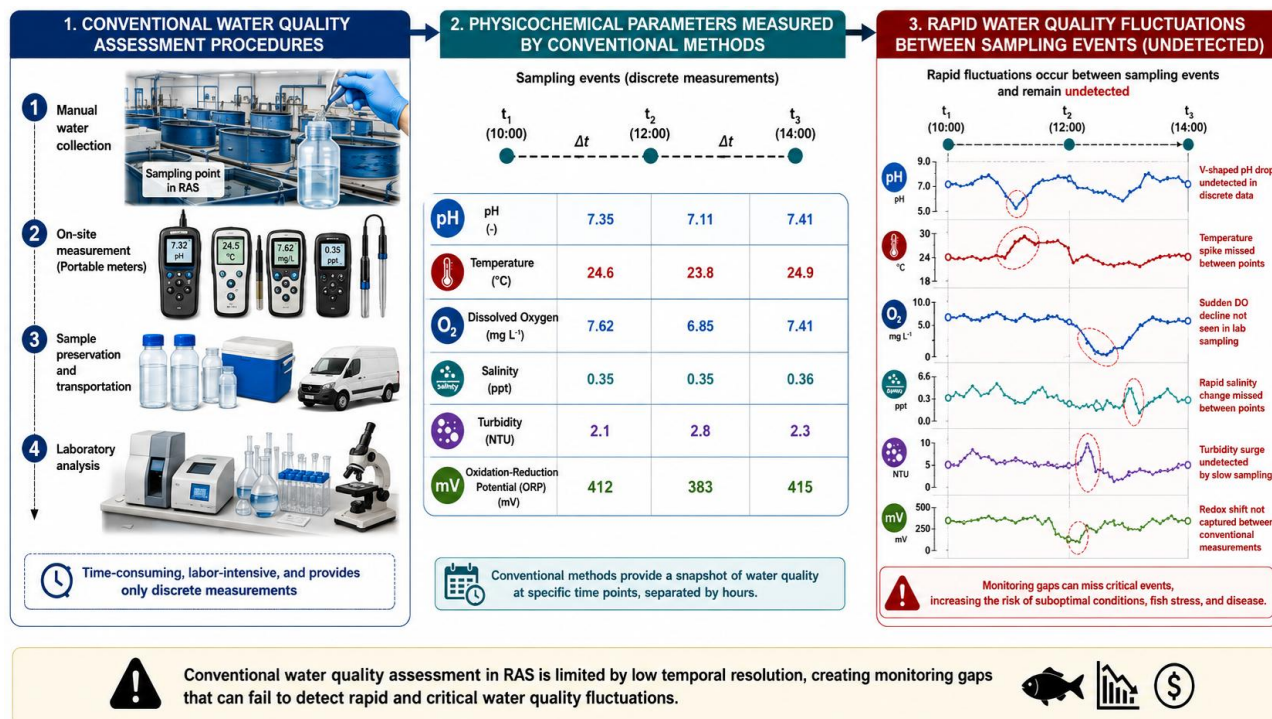


Figure 1 Conventional water quality assessment workflow and temporal limitations in recirculating aquaculture systems

Recent implementations show that IoT-enabled monitoring is becoming more accurate, more distributed, and more operationally practical across aquaculture settings. NB-IoT systems have achieved stable long-distance transmission and accurate control of temperature, dissolved oxygen, and pH, while review evidence shows that real-time monitoring remains the dominant delivered function and that temperature, dissolved oxygen, and pH are the most frequently prioritized variables in IoT-based aquaculture platforms. Even so, these systems still face practical constraints involving calibration, maintenance, automation depth, and performance in remote areas, which explains why many platforms remain focused on monitoring and alerts rather than fully autonomous control (Lindholm-Lehto, 2023; Flores-Iwasaki et al., 2025).

3.3 Data integration and feature extraction for aquaculture management

The next stage of RAS monitoring is not simply collecting more data, but integrating heterogeneous sensor streams into models that can extract useful features for management. Water quality in aquaculture is shaped by nonlinear interactions among fish density, feeding, climate, and interdependent parameters, so predictive systems increasingly use machine learning to capture temporal patterns and forecast variables such as dissolved oxygen and pH before harmful shifts occur (Baena-Navarro et al., 2025). This transition turns data acquisition into decision support by linking real-time monitoring with early warning, trend detection, and operational planning.

Feature extraction is central to this transition because raw time-series signals are often noisy, redundant, and difficult to interpret directly. Hybrid deep-learning frameworks now use convolutional layers to extract local features from timestamped water-quality data and recurrent units such as GRU or LSTM to learn sequential dependencies, while intelligent RAS analytics systems also use relational data analysis to detect sensor faults and infer relative parameter changes with lower hardware requirements (Yang et al., 2023). More broadly, machine learning in aquaculture has expanded beyond water-quality prediction alone to include biomass estimation, fish identification, and behavioral analysis, suggesting that future RAS management will depend on integrated data pipelines that combine environmental sensing with biological response indicators (Singh et al., 2024).

4 Strategies for Water Quality Control in Recirculating Aquaculture Systems

4.1 Mechanical and biological filtration technologies

Mechanical and biological filtration form the core treatment sequence in recirculating aquaculture systems because RAS water contains both suspended solids and dissolved metabolic wastes that must be removed continuously to maintain fish health. Reviews of RAS treatment equipment describe physical filtration units such as microscreen drum filters, foam fractionators, and other solid-liquid separation devices as the main tools for removing residual feed, feces, and fine suspended particles before they impair downstream treatment performance, while the broader water treatment unit is recognized as the central barrier against pollutant accumulation in the recirculating loop (Li et al., 2023). This front-end solids removal step is strategically important because particulate waste is one of the main hazardous fractions generated by feeding and fish excretion, and its early capture reduces organic loading on later biological processes.

Biological filtration then stabilizes water quality by converting toxic nitrogenous wastes into less harmful forms through microbially mediated nitrification. Biofilters are the defining feature of intensive RAS and operate through microbial consortia that oxidize ammonia to nitrate, with nitrifying bacteria growing either in suspension or as biofilms attached to fixed media; accordingly, technologies such as fluidized sand biofilters, moving-bed biofilm reactors, and rotating biological contactors are widely used because they provide the surfaces and hydrodynamic conditions needed for sustained microbial activity. Future optimization of these systems depends not only on reactor design but also on better management of microbial ecology, since biofilter success is ultimately determined by the structure and function of the biological community embedded within the filter matrix.

4.2 Oxygen management and gas exchange regulation

Oxygen management is a central water quality control strategy in RAS because high stocking density and continuous microbial oxidation create strong and variable oxygen demand. Artificial aeration remains essential for maintaining dissolved oxygen at suitable levels, and aerator selection must balance transfer performance with operating cost, while broader dissolved oxygen control research shows that keeping DO near a desired setpoint is important not only for fish health but also for treatment efficiency and energy use (Li et al., 2022). In practice, this means oxygen supply systems must be designed as control technologies rather than simple accessories, with sizing and operation matched to biomass, feed load, and the oxygen demand of biofilters.

Gas regulation in RAS also requires effective removal of carbon dioxide and, increasingly, more precise control architectures for oxygen delivery. Recent work on hybrid degassers shows that excessive CO₂ accumulation and oxygen depletion jointly reduce water quality and production efficiency, and that combined packing-media configurations can improve both CO₂ stripping and oxygenation performance; at the same time, control-system reviews indicate that although predictive, fuzzy, and hybrid DO controllers are being developed, PID-based approaches remain the most widely implemented in engineering practice (Li et al., 2022). Complementary methods such as hydrogen peroxide dosing can also contribute when carefully applied, because they can simultaneously increase oxygen saturation and reduce microbial load without measurable fish stress or biofilter impairment under appropriate conditions.

4.3 Nutrient and waste management approaches

Nutrient and waste management in RAS must address not only ammonia and nitrite toxicity but also the longer-term buildup of nitrate and other dissolved wastes. Conventional indoor RAS typically rely on solids capture followed by nitrification inside the recirculating loop, yet nitrification alone shifts waste from ammonia to nitrate rather than eliminating total nitrogen, which is why nitrogen accumulation remains a major challenge in sustainable high-reuse systems (Preena et al., 2021). This limitation becomes more important as water exchange is reduced, since system sustainability then depends on internal waste reduction rather than dilution.

For that reason, current nutrient management increasingly emphasizes denitrification, anammox, sludge digestion, and biological assimilation pathways that reduce waste mass rather than only transforming it. Denitrification can lower energy and water demand because it reduces the need for aeration and minimizes water exchange, while

coupled nitrification-denitrification systems in biofilters and bioreactors can promote total nitrogen removal through the coexistence of autotrophic nitrifiers, aerobic denitrifiers, anammox organisms, and comammox populations; in parallel, plant uptake and extractive organisms can convert dissolved nutrients into useful biomass, especially in integrated treatment configurations (Preena et al., 2021). Overall, the most effective waste-management strategies are those that integrate nitrogen conversion, sludge handling, and nutrient recovery into one coordinated treatment framework rather than treating each waste stream in isolation.

5 Fish Health Management Under Recirculating Aquaculture Conditions

5.1 Effects of environmental stress on fish growth and immunity

Fish health management in RAS begins with controlling environmental stress because intensive rearing exposes fish to suboptimal water quality, crowding, and handling stressors that impair health and increase disease susceptibility. Broad aquaculture reviews show that intensive systems tend to weaken immune function and reduce performance when environmental conditions deteriorate, making stress reduction a primary requirement for sustainable production rather than a secondary welfare concern (Kari, 2025). In practice, this means that fish growth and immunity in RAS should be interpreted as direct biological responses to the rearing environment.

Experimental RAS evidence confirms that specific physical stressors can alter growth and immune status even when basic water quality is held constant. In turbot, excessive flow velocity reduced growth and antioxidant capacity while activating stress- and immune-related responses, whereas a moderate velocity improved feed intake, specific growth rate, and innate immune indicators, showing that hydraulic conditions themselves can shift fish from adaptive stimulation to chronic stress.

Stocking density is another major environmental driver of fish condition in recirculating systems because it amplifies social stress, metabolic loading, and physiological strain. In juvenile Chinese sturgeon reared in RAS, high density significantly suppressed growth, downregulated growth hormone and IGF-I signaling, and increased cortisol, glucose, lactate, and HSP70 expression, indicating a coordinated stress response linked to impaired somatic performance. The same high-density treatment also depressed antioxidant enzyme activity and reduced serum IgM, lysozyme, alkaline phosphatase, acid phosphatase, and multiple immune-related transcripts, showing that chronic crowding can weaken both oxidative defense and immune competence.

Environmental change in RAS can also produce species- and context-dependent stress responses that are not always maladaptive but still require management. During centrifugal pumping in commercial Atlantic salmon RAS, primary and secondary stress responses were triggered, yet fish maintained homeostasis over the recovery period, while in pikeperch, transfer from pond nursing to RAS dry-feed habituation elicited stronger cortisol and immunoglobulin responses in one generation that appeared to support better adaptation during that phase. These findings indicate that fish health management should distinguish between short-term adaptive responses and prolonged stress that erodes growth, immunity, and resilience.

5.2 Disease prevention and health monitoring strategies

Disease prevention in RAS is most effective when it is organized around preventive health management rather than treatment after outbreaks occur. Epidemiological reviews conclude that no single measure is sufficient and that successful disease control requires a combination of surveillance, biosecurity, immunoprophylaxis, and legally approved therapeutics, while aquaculture management reviews similarly emphasize strict biosecurity as essential as fish movements and intensification raise the risk of pathogen introduction and economic loss. This preventive logic is especially important in recirculating systems because their closed design can allow pathogens to persist once introduced.

Modern RAS health monitoring is therefore shifting toward continuous, non-lethal, and system-level detection methods. Recent salmon work showed that eDNA/eRNA from RAS water can track pathogen dynamics non-invasively and provided strong correlations between water samples and gill swabs for SGPV and ISAV-HPR0, demonstrating that water itself can function as an early diagnostic matrix in recirculating systems. In parallel, IoT-

based monitoring frameworks are being developed to combine real-time sensor data, machine learning, and remote alerts so that water quality deterioration and pathogen indicators can be recognized before disease becomes clinically obvious.

Health monitoring in RAS also needs to include organ-specific and colony-level surveillance because water quality effects do not always present as overt mortality. Gill-focused reviews show that RAS conditions can affect gill health, but current findings are inconsistent partly because many studies inadequately report water quality; they therefore recommend more holistic assessment using histology, pathogen screening, gene expression, and microbiome analysis (Bjørgen et al., 2024). Facility-level programs in recirculating systems likewise emphasize monitoring both individual and population health and preventing pathogen entry and spread through structured biosecurity protocols that can be adapted across facility sizes.

An important emerging opportunity is to use controlled environmental manipulation as part of preventive health management, while recognizing its risks. In a commercial RAS nursery, short-term non-lethal heat shock induced heat shock proteins and appeared to protect fish from opportunistic infection, suggesting that managed environmental-microbial-host interactions can support disease control; however, excessive temperature stress also risked microbiota dysbiosis and mortality, so such approaches require precise control and monitoring (Ng et al., 2024).

5.3 Integration of nutrition and environmental management

Nutrition and environmental management are tightly linked in RAS because dietary adequacy partly determines how fish tolerate water-quality and husbandry stress. Reviews of stress management in aquaculture show that dietary interventions can improve immunocompetence and stress resistance when environmental challenges are unavoidable, and more recent synthesis argues that nutritional immunomodulation is an effective non-pharmaceutical strategy for improving resilience to both pathogens and environmental stressors (Kari, 2025). This makes feeding strategy a central part of fish health management rather than a separate production variable.

The strongest mechanistic evidence points to the roles of vitamins, minerals, amino acids, and other functional feed components in supporting mucosal integrity, antioxidant defense, cytokine activity, and immune cell growth under stress. Earlier reviews found that diets fortified above minimum requirement with selected nutrients, probiotics, prebiotics, and immunostimulants can improve disease resistance, stress tolerance, and reduce reliance on antibiotics, while intestine-focused work emphasizes that balanced diets protect gut barriers and thereby support whole-body immunity. In RAS, where environmental fluctuations can quickly disrupt feeding and microbial balance, these nutritional effects are particularly relevant to maintaining stable health.

Integration also extends to developmental strategy, because nutritional programming can shape later stress tolerance and feed utilization. Early-life dietary interventions have been linked to persistent changes in nutrient use, digestive enzyme activity, and immune responses, and recent reviews argue that species-specific, development-stage-targeted immunonutrition represents a major advance for precision aquaculture (Kari, 2025). This suggests that health management in RAS should begin before grow-out, with feeding protocols designed to prepare fish for intensive recirculating conditions.

At the system level, integrating nutrition with environmental control aligns fish health goals with broader sustainability goals. Dynamic RAS models show that management decisions can be linked to predicted fish growth and mortality under different environmental conditions, while nutrition-sensitive aquaculture frameworks argue that production systems should optimize animal performance and health without compromising environmental sustainability and human wellbeing (Kamali et al., 2022). Overall, effective fish health management in RAS depends on coordinated control of rearing conditions, preventive monitoring, and precision nutrition rather than on any single intervention alone.

6 Case Study: Integrated Water Quality Control and Fish Health Management in a Commercial RAS Facility

6.1 System design and monitoring framework

A commercial RAS case study is best framed as a multi-unit control system in which tank performance depends on both water treatment design and continuous monitoring. Field and facility evaluations show that practical RAS layouts combine fish tanks with dedicated treatment and purification units, and that clear description of water process flow, treatment components, and species-specific water quality limits is essential for benchmarking performance and refining future commercial designs. This design logic matters because effective facility evaluation requires not only acceptable production outcomes but also explicit performance standards for water quality and system function across operating conditions (Mota et al., 2022).

Within that framework, the monitoring system in a commercial RAS must follow the variables most tightly linked to fish stress and operational failure. Reviews and commercial-scale monitoring studies agree that temperature, pH, dissolved oxygen, and related nitrogen compounds must be kept within narrow ranges, while recent kingfish data show that CO₂, pH, temperature, nitrogen compounds, and hydrogen sulfide can be maintained within published safety thresholds when monitoring is systematic and sustained. The same evidence base also shows that monitoring is moving from periodic handheld testing toward automated, real-time acquisition, because conventional lagged measurements are poorly suited to intensive systems where pump or aerator failure can trigger rapid oxygen depletion and water quality deterioration (Figure 2) (Lindholm-Lehto, 2023; Malandrakis, 2025).

6.2 Analysis of water quality variation and fish performance responses

Commercial and near-commercial RAS studies show that water quality variation is not biologically neutral, because shifts along the treatment train and over time translate into measurable differences in fish performance. In an integrated land-based RAS, water quality changed gradually along the direction of flow, and fish production responded to those differences through variation in final weight, survival, specific growth rate, and yield. Correlation analysis in that system further showed that the main cultured species performed better under mesotrophic or oligotrophic conditions, indicating that performance responses depend on how well local water conditions match species-specific tolerances.

Temporal variability inside RAS is also uneven across parameter classes, which has direct implications for fish health interpretation and management. In Atlantic salmon research facilities, sensor-controlled parameters showed relatively low variation, whereas parameters dependent on biofilter maturation and performance varied much more strongly, and variation among experimental trials exceeded variation within trials (Mota et al., 2022). Complementary dynamic modeling indicates that growth and mortality relationships can be used to predict fish well-being under changing environmental conditions and management strategies, supporting the use of water-quality variation as a leading indicator of both welfare risk and production efficiency (Kamali et al., 2022).

6.3 Development of intelligent management strategies

The next step in a commercial RAS case study is to convert monitoring into intelligent management, where sensor data drive adaptive interventions rather than passive record-keeping. Commercial-scale control research shows that reinforcement-learning architectures can combine feeding optimization with water quality management, using modular design, robust sensor networks, and fault-tolerant control to maintain fish growth and stable environmental conditions across large facilities. Performance gains from this approach are substantial, with reported improvements including 15.5% better feed conversion, 96.8% water-quality maintenance, and 31.5% lower operational cost, indicating that integrated control can improve both biology and economics (Elmessery et al., 2025).

Intelligent management also increasingly includes automated interventions, predictive analytics, and behavior-linked control. IoT-ML systems have supported more than 6000 corrective interventions, including automated oxygenation and pH adjustment, while maintaining survival above 90% under challenging seasonal conditions, and deep learning-based aeration control has reduced energy use while accelerating growth under stable water quality conditions (Baena-Navarro et al., 2025). Even so, the literature remains cautious: AI-assisted imaging, behavior

monitoring, and predictive tools are advancing quickly, but some reviews note that many machine-learning systems are still validated mainly in smaller tanks rather than fully commercial RAS scales (Gupta et al., 2024).

RECIRCULATING AQUACULTURE SYSTEM (RAS)

System Configuration and Water Treatment Pathway

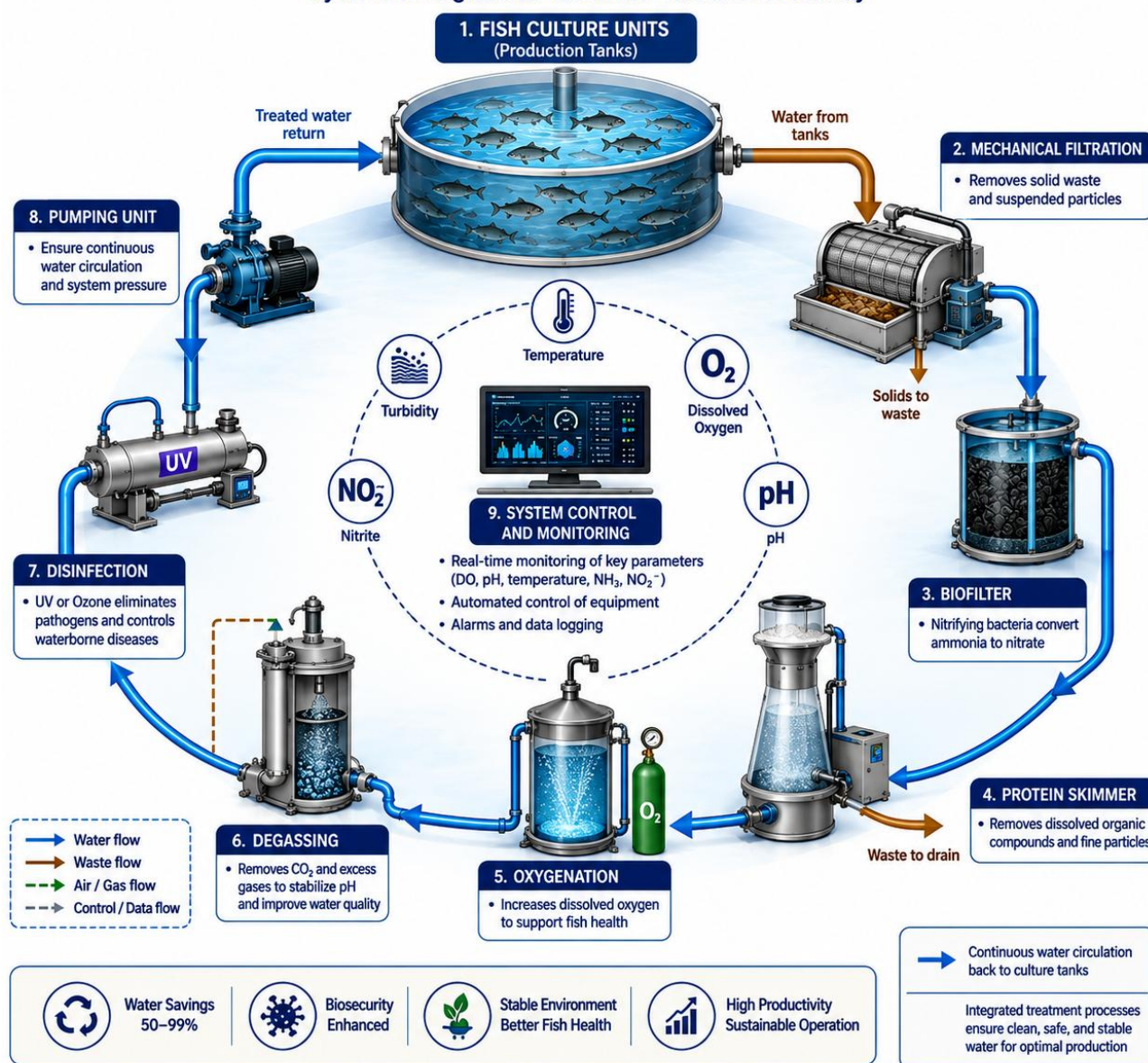


Figure 2 Structural configuration and water treatment pathway of a commercial recirculating aquaculture system

7 Intelligent Technologies and Future Development of RAS Management

7.1 Artificial intelligence and predictive modeling for aquaculture management

Artificial intelligence is becoming a core tool in RAS management because water quality control increasingly depends on predicting system change before biological stress or equipment failure occurs. Recent RAS-focused work argues that future water status must be forecast in advance to support control strategy generation in multi-unit systems, while broader AIoT reviews show that predictive models such as LSTM and related methods are already being used to monitor dissolved oxygen, pH, and temperature for real-time intervention (Yang et al., 2023). This shift matters because predictive management turns monitoring from passive observation into active decision support, allowing farmers to anticipate instability rather than merely respond to it after thresholds are crossed (Huang and Khabusi, 2025).

Current predictive models in aquaculture are increasingly designed to reduce redundant inputs and extract the most informative features from complex time-series data. Hybrid deep-learning frameworks for RAS combine convolutional layers, recurrent units, and attention mechanisms so that local patterns, sequential dynamics, and critical features can be learned together, while feature-selection work in outdoor recirculation systems shows that a small subset of routinely measured variables can effectively support prediction of dissolved oxygen, TAN, nitrite, and alkalinity (Jongjaraunsuk et al., 2024). Even so, predictive performance remains parameter-specific, since the same outdoor study found strong prediction for several variables but substantially weaker performance for pH, indicating that model reliability still depends on the biological and chemical behavior of the target parameter (Yang et al., 2023).

AI is also expanding beyond water chemistry prediction into growth modeling and operational optimization. In a smart aquaculture management system, deep learning linked environmental and system parameters to California bass growth with high predictive accuracy, and the resulting model was proposed for integration into autonomous feeding to reduce leftover feed. More generally, systematic reviews conclude that AI now supports decision-making, optimization, and automation across feeding, disease monitoring, production modeling, and environmental management, suggesting that future RAS platforms will increasingly connect fish performance prediction with water-quality control in a single analytical framework (Aung et al., 2024).

AI-based analytics are also being adapted for practical use in lower-cost and resource-constrained environments rather than only in highly capitalized farms. IoT-linked analytics systems have identified strong correlations among water variables, including substantial associations of pH with dissolved oxygen and temperature, which can guide simpler predictive control rules, while other smart aquaculture systems report that Random Forest models can outperform alternative algorithms for classification-based water-quality prediction tasks (Matkarimov et al., 2025). This suggests that the future of predictive RAS management will likely include both advanced deep-learning architectures for large datasets and lighter-weight models that are easier to deploy where infrastructure, computing capacity, or technical expertise are limited.

7.2 Automation and smart control systems in RAS

Automation in RAS is moving from isolated sensors toward connected systems that both detect change and trigger corrective action. Recent reviews note that many farms still rely on manual measurements or disconnected devices despite the availability of real-time sensing, while cost-effective RAS platforms now outline the transition from passive monitoring to closed-loop control through continuous feedback, error calculation, and actuator commands (Grandez-Yoplac et al., 2025). In this architecture, smart control depends on linking sensors, communication networks, cloud or edge processing, and actuators into a single operational loop rather than treating monitoring and intervention as separate tasks (Malandrakis, 2025).

Prototype and commercial-oriented systems already show how this logic can be implemented in practice. RAS automation platforms based on Raspberry Pi, cloud connectivity, and modular sensor networks have been designed to support real-time acquisition, intelligent aeration, and visualization, while a tilapia RAS prototype automatically monitored and controlled pH, temperature, salinity, and dissolved oxygen with measurements accessible through a web application (Libao et al., 2024). These systems indicate that smart RAS control is no longer limited to theory, because they connect environmental sensing directly to user interfaces and operational responses that can be accessed remotely (Shodiq et al., 2023).

A central benefit of automation is that it reduces the biological risk created by delayed human response. Recent IoT monitoring reviews report that sensor-based water monitoring improves growth, reduces mortality, and enables rapid prediction and detection of atypical TAN levels, while integrated IoT-ML systems have carried out thousands of corrective interventions and maintained fish survival above 90% under demanding conditions (Baena-Navarro et al., 2025; Flores-Iwasaki et al., 2025). This matters particularly in RAS because pumps and aerators are life-support components, and automation can shorten the time between deviation detection and intervention when oxygen depletion or ammonia accumulation develops rapidly (Malandrakis, 2025).

Automation is also broadening from water-quality regulation to behavior-linked and vision-based management. Reviews of recent RAS developments describe AIoT systems that reduce manpower and machine-vision tools that detect altered swimming behavior as an early warning of suboptimal water conditions, including hydrogen sulfide exposure below the known toxicity threshold (Gupta et al., 2024). Together with smart feeding systems that improve feed conversion and growth while reducing waste, these tools indicate that the next phase of RAS automation will combine environmental control with behavioral sensing and production optimization rather than focusing on physicochemical variables alone (Huang and Khabusi, 2025).

7.3 Challenges and future perspectives

The main barriers to intelligent RAS adoption remain economic, technical, and organizational rather than conceptual. Recent reviews describe high installation cost, connectivity problems in rural areas, and demanding calibration and maintenance requirements as major obstacles to smart RAS implementation, while earlier industry analysis identified poor system design and weak management capacity, especially the shortage of skilled personnel responsible for water quality and mechanical issues, as persistent constraints on RAS performance. These barriers explain why intelligent technologies have advanced faster in research and prototypes than in broad commercial uptake (Grandez-Yoplac et al., 2025).

A second major challenge is scale, robustness, and data quality. AI and IoT reviews emphasize that widespread deployment is still limited by restricted access to representative datasets, expensive sensor and AI infrastructure, and technical complexity, while water-quality management reviews further note persistent issues with sensor biofouling, recalibration, and performance across diverse environments (Aung et al., 2024). The future direction is therefore not simply more algorithm development, but more transferable systems that are resilient under real farm variability and that can operate reliably with local maintenance capacity (Huang and Khabusi, 2025).

Energy use and sustainability will also shape the future of intelligent RAS management. Although RAS are highly water-efficient and relatively insulated from climate variability, energy consumption and greenhouse gas emissions remain major limiting factors, and broader systems analyses argue that renewable energy integration combined with advanced monitoring and process optimization could improve both environmental and economic feasibility. Future intelligent RAS will therefore likely be judged not only by how well they stabilize water quality and fish health, but also by how effectively they reduce energy demand through system-wide optimization (Ahmed and Turchini, 2021).

The strongest near-term development pathway combines better sensing, tighter automation, and broader biological data integration. Proposed priorities include self-calibrating multi-parameter sensors, low-power communication technologies such as LoRaWAN and NB-IoT, and expansion of monitored variables to include microbiological and emerging-contaminant indicators, all of which would support more comprehensive and autonomous environmental control (Baena-Navarro et al., 2025). More broadly, recent RAS reviews describe a thematic shift from classical engineering variables toward proteomics, transcriptomics, and molecular techniques, suggesting that future intelligent management will increasingly fuse environmental monitoring with microbial and genomic evidence for disease control, growth optimization, and precision aquaculture (Grandez-Yoplac et al., 2025).

8 Conclusions

Recent advances in water quality control technologies for RAS show a clear transition from conventional treatment and intermittent measurement toward integrated, real-time, and more intelligent control systems. Current RAS performance depends on coordinated use of mechanical and biological filtration, gas regulation, disinfection, and monitoring tools that remove suspended solids, nitrogenous wastes, carbon dioxide, and other hazardous compounds while maintaining conditions suitable for fish growth. At the same time, modern monitoring has expanded from labor-intensive handheld sampling to sensor-based surveillance, IoT connectivity, and AI-assisted warning systems that improve the speed and precision of operational responses.

Technological progress is also moving beyond basic recirculation toward process intensification and adaptive optimization. Dynamic and reinforcement-learning models now link feeding, oxygenation, biofilter behavior, and

water chemistry, allowing managers to anticipate parameter changes and maintain higher water-quality stability under changing operational loads. In parallel, targeted treatment innovations such as side-loop denitrification, sand filtration, and advanced oxidation have improved nutrient removal and water reuse, although some promising methods still require caution because water-quality gains can be accompanied by emerging risks such as instability over time or increased antibiotic resistance genes.

The literature consistently shows that water quality management and fish health protection are inseparable in RAS. Fish health in recirculating systems is directly shaped by the quality of the production water, while the accumulation of ammonia, nitrite, carbon dioxide, organic matter, and other hazardous compounds can compromise growth, welfare, and survival if treatment performance declines. This linkage is especially important because opportunistic pathogens remain difficult to manage in RAS, and some conventional chemotherapeutic approaches can themselves disrupt biofilters and further destabilize water quality.

An integrated health-protection strategy therefore requires not only good engineering control, but also biological surveillance and multi-level assessment. Changes in water quality are reflected in fish behavior and can support early detection of stress, while more comprehensive health monitoring increasingly includes histology, pathogen screening, gene expression, and microbiome-based assessment of gill condition and mucosal health. Across the broader RAS literature, this integration is now reinforced by digital tools that connect environmental monitoring with predictive modeling, welfare indicators, and management decisions aimed at sustaining both fish performance and biosecurity.

Future opportunities for sustainable recirculating aquaculture lie in combining digitalization, circular resource use, and lower-impact system design. RAS already offers major sustainability advantages through reduced water use, improved waste management, nutrient recycling, and reduced exposure to climate variability, but wider adoption still depends on making systems more energy-efficient, more affordable, and easier to manage at commercial scale. The next generation of sustainable RAS will likely depend on better integration of smart sensing, autonomous control, and predictive models that reduce risk while improving resource efficiency and operational consistency.

A second major opportunity is to close the RAS loop more completely by recovering value from waste streams rather than treating them only as disposal problems. Integrated farming approaches, including aquaponics, wetlands, algal systems, and microalgae-based nutrient recovery, can recycle nitrogen and phosphorus, generate useful co-products, and improve the environmental and economic performance of land-based fish production. Overall, the future of RAS will depend on how effectively the sector combines advanced water-quality control, fish-health-centered management, and circular bioeconomy strategies to produce seafood with lower environmental cost and greater long-term resilience.

References

- Ahmed N., and Turchini G., 2021, Recirculating aquaculture systems (RAS): Environmental solution and climate change adaptation, *Journal of Cleaner Production*, 297: 126604.
<https://doi.org/10.1016/j.jclepro.2021.126604>
- Aung T., Razak A.R., and Nor A.R.B.M., 2024, Artificial intelligence methods used in various aquaculture applications: A systematic literature review, *Journal of the World Aquaculture Society*, 56(1): e13107.
<https://doi.org/10.1111/jwas.13107>
- Baena-Navarro R., Carriazo-Regino Y., Torres-Hoyos F., and Pinedo-López J., 2025, Intelligent prediction and continuous monitoring of water quality in aquaculture: Integration of machine learning and Internet of Things for sustainable management, *Water*, 17(1): 82.
<https://doi.org/10.3390/w17010082>
- Björger H., Koppang E., and Nowak B.F., 2024, Gill health in fish farmed in recirculating aquaculture systems (RAS): A review, *Journal of Fish Diseases*, 48(3): e14057.
<https://doi.org/10.1111/jfd.14057>
- Dai L., Chen Y., and Li C., 2025, Environmental factor impacts on behavioral and physiological responses of aquaculture species in recirculating aquaculture systems: Mechanisms and regulation, *Aquaculture Reports*, 44: 103036.
<https://doi.org/10.1016/j.aqrep.2025.103036>

- Elmessery W.M., Abdallah S.E., Oraith A.A.T., Espinosa V., Abuhussein M.F.A., Szűcs P., Eid M.H., El-Shinawy D.M., Aljumayi H., Mahmoud S.F., and Elwakeel A.E., 2025, A deep deterministic policy gradient approach for optimizing feeding rates and water quality management in recirculating aquaculture systems, *Aquaculture International*, 33(4): 253.
<https://doi.org/10.1007/s10499-025-01914-z>
- Flores-Iwasaki M., Guadalupe G.A., Pachas-Caycho M., Chapa-Gonza S., Mori-Zabarburú R.C., and Guerrero-Abad J., 2025, Internet of Things (IoT) sensors for water quality monitoring in aquaculture systems: A systematic review and bibliometric analysis, *AgriEngineering*, 7(3): 78.
<https://doi.org/10.3390/agriengineering7030078>
- Grandez-Yopla D.E., Pachas-Caycho M., Cristobal J., Chapa-Gonza S., Mori-Zabarburú R.C., and Guadalupe G.A., 2025, Recirculating aquaculture systems (RAS) for cultivating *Oncorhynchus mykiss* and the potential for IoT integration: A systematic review and bibliometric analysis, *Sustainability*, 17(15): 6729.
<https://doi.org/10.3390/su17156729>
- Gupta S., Makridis P., Henry I., Velle-George M., Ribicic D., Bhatnagar A., Skalska-Tuomi K., Daneshvar E., Ciani E., Persson D., and Netzer R., 2024, Recent developments in recirculating aquaculture systems: A review, *Aquaculture Research*, 2024(1): 6096671.
<https://doi.org/10.1155/are/6096671>
- Holan A.B., Good C., and Powell M., 2020, Health management in recirculating aquaculture systems (RAS), In *Aquaculture Health Management: Fish Health and Veterinary Medicine*, 2020: 281-318.
<https://doi.org/10.1016/B978-0-12-813359-0.00009-9>
- Huang Y.P. and Khabusi S.P., 2025, Artificial intelligence of things (AIoT) advances in aquaculture: A review, *Processes*, 13(1): 73.
<https://doi.org/10.3390/pr13010073>
- Islam S.I., Ahammad F., and Mohammed H.H., 2024, Cutting-edge technologies for detecting and controlling fish diseases: Current status, outlook, and challenges, *Journal of the World Aquaculture Society*, 55(2): e13051.
<https://doi.org/10.1111/jwas.13051>
- Jongjaraunsuk R., Taparhudee W., and Suwannasing P., 2024, Comparison of water quality prediction for red tilapia aquaculture in an outdoor recirculation system using deep learning and a hybrid model, *Water*, 16(6): 907.
<https://doi.org/10.3390/w16060907>
- Kamali S., Ward V., and Ricardez-Sandoval L., 2022, Dynamic modeling of recirculating aquaculture systems: Effect of management strategies and water quality parameters on fish performance, *Aquacultural Engineering*, 99: 102294.
<https://doi.org/10.1016/j.aquaeng.2022.102294>
- Kari A.Z., 2025, Nutritional immunomodulation in aquaculture: Functional nutrients, stress resilience, and sustainable health strategies, *Aquaculture International*, 33(6): 441.
<https://doi.org/10.1007/s10499-025-02122-5>
- Li D., Zou M., and Jiang L., 2022, Dissolved oxygen control strategies for water treatment: A review, *Water Science and Technology*, 86(6): 1444-1466.
<https://doi.org/10.2166/wst.2022.281>
- Libao F.J.D., Villaverde O.S.M., De Luna N.A.P.U., Comedia V.J.G., Luna M.O., Atienza A.M.C., and Espeña G.D., 2024, Automated control and IoT-based water quality monitoring system for a *Molobicus tilapia* recirculating aquaculture system (RAS), 2024 IEEE Conference on Technologies for Sustainability (SusTech), 2024: 410-415.
<https://doi.org/10.1109/SusTech60925.2024.10553538>
- Lindholm-Lehto P., Pulkkinen J., Kiuru T., Koskela J., and Vielma J., 2020, Water quality in recirculating aquaculture system using woodchip denitrification and slow sand filtration, *Environmental Science and Pollution Research*, 27(14): 17314-17328.
<https://doi.org/10.1007/s11356-020-08196-3>
- Malandrakis E., 2025, Design and implementation of a cost-effective IoT-based monitoring and alerting system for recirculating aquaculture systems (RAS), *Sensors*, 25(21): 6692.
<https://doi.org/10.3390/s25216692>
- Matkarimov I., Hwsein R.R., Matyakubov M., Bhaskaran B., Eshbekova D., and Vij P., 2025, Intelligent IoT-enabled data analytics and monitoring framework for smart freshwater recirculating aquaculture systems, *International Journal of Aquatic Research and Environmental Studies*, 2025: 22-29.
<https://doi.org/10.70102/ijares/v5s1/5-s1-03>
- Mota V., Striberny A., Verstege G.C., Difford G., and Lazado C., 2022, Evaluation of a recirculating aquaculture system research facility designed to address current knowledge needs in Atlantic salmon production, *Frontiers in Animal Science*, 3: 876504.
<https://doi.org/10.3389/fanim.2022.876504>
- Ng T.H., Sobana M., Chew X.Z., Madhavan T.N.D., Chow J.W., Low A., Seedorf H., and Gomes B.G., 2024, Dissecting the heat stress altering immune responses and skin microbiota in fish in a recirculating aquaculture system in Singapore, *bioRxiv*, 2024: 2024.01.02.573918.
<https://doi.org/10.1101/2024.01.02.573918>
- Pepe-Victoriano R., Pepe-Vargas P., Pérez-Aravena A., Aravena-Ambrosetti H., Huanacuni J.I., Méndez-Abarca F., Olivares-Cantillano G., Acosta-Angulo O., and Espinoza-Ramos L., 2025, Evaluation of water quality in the production of rainbow trout (*Oncorhynchus mykiss*) in a recirculating aquaculture system (RAS) in the Precordilleran Region of Northern Chile, *Water*, 17(11): 1685.
<https://doi.org/10.3390/w17111685>

- Preena P.G., Kumar V.R.J., and Singh I., 2021, Nitrification and denitrification in recirculating aquaculture systems: The processes and players, Reviews in Aquaculture, 13(4): 2053-2075.
<https://doi.org/10.1111/raq.12558>
- Shodiq M., Kusuma D.H., Fitrawan A.A., and Lusi N., 2023, Design of recirculating aquaculture monitoring system based on Internet of Thing and machine learning algorithms, Advances in Mechanical Engineering, Industrial Informatics and Management (AMEIIM2022), 2828(1): 120004.
<https://doi.org/10.1063/5.0164090>
- Singh M., Sahoo K., and Gandomi A.H., 2024, An intelligent-IoT-based data analytics for freshwater recirculating aquaculture system, IEEE Internet of Things Journal, 11(3): 4206-4217.
<https://doi.org/10.1109/JIOT.2023.3298844>
- Udayakumar R., Kadirov I., Radjabova D., Fallah M.H., Tursunov M., and Masalieva O., 2025, A system dynamics model for water quality management in recirculating aquaculture systems (RAS), Natural and Engineering Sciences, 10(2): 434-446.
<https://doi.org/10.28978/nesciences.1763840>
- Yang J., Jia L., Guo Z., Shen Y., Mou Z.J., Yu K., and Lin J.C.W., 2023, Prediction and control of water quality in recirculating aquaculture system based on hybrid neural network, Engineering Applications of Artificial Intelligence, 121: 106002.
<https://doi.org/10.1016/j.engappai.2023.106002>



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Feature Review

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Computational Analysis of Growth Performance and Feeding Efficiency in Aquaculture Species

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Abstract The rapid expansion of aquaculture production has increased the demand for efficient approaches to optimize growth performance and feeding management. Computational analysis provides powerful tools for understanding complex interactions among biological traits, nutritional factors, and environmental conditions in cultured aquatic species. This review summarizes recent advances in mathematical modeling, statistical analysis, machine learning, and artificial intelligence applications for evaluating growth dynamics and feeding efficiency in aquaculture systems. Key production indicators, including weight gain, specific growth rate, feed conversion ratio, and nutrient utilization efficiency, are analyzed through computational frameworks integrating feeding records, environmental monitoring, and physiological responses. Growth prediction models, nonlinear growth simulations, and machine learning algorithms are discussed for their ability to identify critical factors affecting production outcomes and improve management decisions. A case study of Pacific white shrimp (*Litopenaeus vannamei*) demonstrates the application of computational models in predicting growth performance and optimizing feeding strategies under different culture conditions. Furthermore, the integration of computational technologies with IoT-based monitoring and precision aquaculture systems provides new opportunities for reducing feed waste, enhancing production efficiency, and promoting sustainable aquaculture development. Future research should focus on developing more accurate, interpretable, and adaptive models that integrate multi-source biological and environmental data.

Keywords Computational analysis; Aquaculture species; Growth performance; Feeding efficiency; Machine learning models

1 Introduction

Aquaculture has become a central component of the global food system and is now expected to shoulder much of the future increase in aquatic food supply. Over the past two decades, the sector has expanded through intensification, improved feeds, stronger production management, and better biosecurity, while inland aquaculture in Asia has contributed especially strongly to global food security (Naylor et al., 2021). This growth has been driven in part by the limits of capture fisheries and by rising demand for nutrient-dense aquatic foods, making aquaculture one of the fastest-growing food production sectors worldwide and a key pathway for narrowing the global protein supply gap. Yet expansion alone is not sufficient. As fed aquaculture becomes a larger share of production, improving growth performance and feeding efficiency has become one of the industry's most important technical and economic priorities. Feed commonly represents the largest operating cost in many fish production systems, and inefficient feed use increases waste outputs, raises environmental burdens, and reduces profitability. For this reason, indicators such as growth rate, feed conversion ratio, and feed efficiency are no longer viewed simply as farm-level performance measures, but as strategic indicators linking biological productivity with sustainability, resource use, and the long-term resilience of aquaculture systems.

The biological basis of growth performance and feeding efficiency in aquaculture species is complex because these traits emerge from interactions among genetics, physiology, nutrition, environment, and behavior. At the molecular level, fish growth is strongly regulated by the hypothalamic-pituitary-somatotropic axis, particularly through growth hormone and insulin-like growth factor-I, while external variables such as diet, temperature, salinity, photoperiod, pollutants, and stocking density can alter gene expression within this pathway and thereby modify growth outcomes. Growth regulation also depends on broader integrated networks that include epigenetic mechanisms, developmental plasticity, and signaling pathways beyond GH-IGF, which helps explain why growth responses differ across species

and culture environments (Şerban et al., 2025). Nutrition further shapes these outcomes by influencing digestive efficiency, metabolic allocation, gut health, and appetite regulation. Early nutritional programming can produce persistent effects on nutrient utilization, enzyme activity, immunity, and later growth, while specific dietary interventions can improve protein deposition and resilience to environmental stress. In addition, recent work has shown that feeding behavior itself is closely tied to growth performance, with faster feeding activity, stronger appetite signaling, and altered brain expression of orexigenic factors associated with improved growth in cultured carp. Taken together, these findings indicate that feeding efficiency is not a single isolated trait, but rather the phenotypic expression of interconnected biological processes operating across multiple organizational levels.

A further layer of complexity arises because feeding efficiency is also mediated by the digestive and microbial environment, the quality and acceptability of formulated diets, and dynamic responses to husbandry conditions. In practical aquaculture, the transition from traditional feeds to compound diets often exposes major differences in feed acceptance and performance, and these differences can substantially alter production cost and culture duration. In one marine species, poor acceptance of formulated feed was associated with slower production progress, whereas integrating microbiome and metabolome data revealed key microbial-metabolite signatures linked to better feed conversion and growth performance. Similar evidence from systems-level prediction studies shows that feed efficiency is difficult to measure directly in individual fish and cannot be adequately explained by single biomarkers alone; instead, integrated models using proteomic, metabolomic, microbiomic, and clinical covariates provide better predictive power than single-layer data (Young et al., 2023). These results support the view that growth and feed utilization are emergent traits arising from many weakly and strongly interacting factors. They also reveal why conventional empirical management, although still useful, is often insufficient for optimizing modern aquaculture systems in which biological regulation, feed formulation, animal behavior, and environmental variability must all be considered simultaneously.

Against this background, computational analysis provides a necessary framework for transforming complex aquaculture data into actionable knowledge on growth performance and feeding efficiency. Recent studies show that machine learning, deep learning, and adaptive statistical modeling can predict growth trajectories, feed intake, and feed conversion outcomes with useful accuracy when they integrate biological, environmental, and management data. Transformer-based growth models trained on Monte Carlo-generated datasets have reported low prediction errors for fish weight and growth rate, while algorithmic feeding systems combining visual monitoring and multimodal reasoning have improved feed conversion ratio and specific growth rate in recirculating systems (Lan et al., 2025). Likewise, automated feeder research in barramundi has shown that nonlinear and multimodel approaches can explain daily feed intake accurately by combining environmental, fish, feed-composition, and pellet-characteristic variables, reinforcing the value of integrated computational frameworks for precision feeding. Therefore, the objective of this paper is to develop a computational perspective on how growth performance and feeding efficiency can be analyzed across aquaculture species using multidimensional biological and production data. The research framework focuses on three linked tasks: identifying the major biological and environmental determinants of growth and feed utilization, evaluating quantitative indicators and predictive variables associated with performance, and summarizing computational methods capable of supporting precision feeding, selective improvement, and sustainable production management. In this way, computational analysis is positioned not merely as a technical tool, but as a bridging framework that connects biological understanding with practical decision-making in modern aquaculture.

2 Data Acquisition and Computational Framework for Aquaculture Growth Analysis

2.1 Sources and characteristics of aquaculture production datasets

Aquaculture growth analysis relies on datasets that combine biological, environmental, and management information collected at different temporal and spatial scales. At the farm level, production datasets often include fish weight, feeding decisions, and pond- or workshop-specific operating conditions, because differences in environment, equipment, and operator behavior can cause substantial deviations in growth characteristics across culture units (Li et al., 2021). More recent smart-aquaculture studies have expanded these records by linking real-

world growth observations to IoT monitoring systems and open weather datasets, allowing probability-based modeling of key growth drivers under variable environmental conditions (Lan et al., 2025).

The main characteristic of these datasets is their heterogeneity, which makes both data integration and model selection critical. Some studies are based on long historical production series and external covariates such as climate variables, as shown by forecasting work that used 20 years of fish production and climatic data for model training and testing (Rahman et al., 2021). Other studies emphasize that aquaculture development can only be fully explained when production data are integrated with broader social, economic, governance, and environmental indicators, as demonstrated by cross-country datasets containing 42 indicators across 150 countries.

2.2 Computational methods for growth performance evaluation

Growth performance evaluation in aquaculture still begins with classical growth indicators, but computational analysis increasingly favors models that can represent the full growth trajectory. Common descriptive measures such as absolute, relative, and specific growth rates remain useful for basic reporting, yet they simplify growth because they rely mainly on stocking and harvest values and often ignore intermediate observations. For this reason, nonlinear growth functions and species-fitted models are preferred when the goal is realistic prediction of stock development, harvest planning, feeding cost calculation, and production scheduling.

More advanced evaluation methods are designed to handle practical limitations in aquaculture datasets, especially incomplete sampling and farm-level variation. A Bayesian hierarchical approach applied to shrimp growth showed that incomplete or limited aquaculture data can bias nonlinear growth parameters, and that hierarchical correction improved predictive accuracy to 95.76% at pond level and 85.71% at production-cycle level (Zarzar et al., 2023). At the same time, multi-omics work on feed efficiency showed that complex performance traits are better predicted when multiple biological data layers are integrated, with combined random-forest models outperforming any single data layer for feed-efficiency prediction (Young et al., 2023).

2.3 Advanced computational tools for aquaculture production prediction

Advanced prediction tools in aquaculture increasingly combine machine learning, deep learning, and simulation to forecast growth, feeding demand, and production outcomes. Comparative forecasting studies show that time-series methods such as ARIMA, linear regression, random forest, LSTM, and Prophet can all be applied to production prediction, but simpler statistical or machine-learning models sometimes outperform deep learning on univariate aquaculture time series (Nazmi et al., 2023). In parallel, neural-network forecasting for regional aquatic production found that nonlinear methods are well suited to this problem, with an RBF neural network outperforming BP, GA-BP, and LSTM models in prediction accuracy (Hu et al., 2025).

A second major direction is the use of intelligent sensing, vision systems, and simulation-based digital tools for real-time decision support. Computer-vision feeding systems can quantify fish appetite and support automatic feed control, and a near-infrared neuro-fuzzy method achieved 98% feeding-decision accuracy while reducing feed conversion rate by 10.77% compared with a feeding table. Beyond sensing alone, simulation frameworks now incorporate schooling behavior, dynamic energy budgets, and feeding-distribution rules to predict growth trajectories, evaluate the effects of feeding strategies on feed efficiency, and identify management options before live trials are conducted (Takahashi and Komeyama, 2023; Takahashi et al., 2026).

3 Computational Modeling of Growth Performance in Aquaculture Species

3.1 Mathematical modeling of growth dynamics

Mathematical modeling of aquaculture growth has moved from simple descriptive indices toward dynamic functions that can represent organism development over time. Traditional indicators such as absolute, relative, and specific growth rate remain widely used because they are easy to compute, but they simplify growth by relying mainly on stocking and harvest values and by ignoring intermediate observations. For this reason, nonlinear growth functions are preferred when the goal is realistic prediction across life stages, and the von Bertalanffy growth function remains one of the most commonly used formulations because it links observed size change to an underlying bioenergetic interpretation.

More mechanistic approaches seek to model growth as the result of energy acquisition and allocation rather than curve fitting alone. Bioenergetic formulations can incorporate environmental drivers into growth equations and help explain density-dependent and time-varying growth patterns, which makes them more informative than purely empirical trend models for scenario analysis. Dynamic energy budget models extend this logic by representing ingestion, assimilation, maintenance, and growth as connected metabolic processes, and recent aquaculture applications have shown that such models can predict measurable outputs such as weight gain, respiration, and waste production under different temperatures, feeding levels, and diet compositions (Stavrakidis-Zachou et al., 2025).

3.2 Environmental and physiological drivers affecting growth prediction

Growth prediction in aquaculture depends strongly on environmental variables because fish and crustaceans respond directly to changes in water quality and culture conditions. Temperature, dissolved oxygen, pH, ammonia, nitrite, nitrate, stocking density, and feeding regime all influence body weight, feed intake, feed conversion, survival, and health, so growth models that omit these covariates are likely to lose predictive accuracy (El-Hack et al., 2022). In intensive systems such as recirculating aquaculture, these factors must be controlled within appropriate ranges, and even light environment can alter feeding behavior, growth rate, survival, and feed conversion, showing that growth prediction must be built on multivariable environmental monitoring rather than on temperature alone (Li et al., 2021).

Physiological regulation adds another layer of complexity because growth is not only environmentally constrained but also biologically mediated. The GH-IGF-I axis is a central regulatory system for fish growth, and its expression changes with diet, photoperiod, salinity, pollutants, and stocking density, which means that environmental effects on growth often operate through endocrine and metabolic pathways rather than through direct physical stress alone. Temperature is especially important because it acts as a master abiotic factor that controls development and physiology, while extreme thermal events can alter metabolism, immunity, osmotic balance, and overall physiological fitness, thereby changing growth trajectories in ways that are species- and context-dependent.

3.3 Machine learning-based prediction of growth performance

Machine learning models are increasingly used to predict aquaculture growth because they can integrate many interacting predictors without requiring a fixed mechanistic structure. Review evidence shows that machine learning has become an important tool in intelligent aquaculture for biomass evaluation, behavioral analysis, and water-quality prediction, while more recent deep-learning reviews identify growth prediction as one of the main application areas alongside health monitoring and intelligent feeding (Wu et al., 2025). These methods are especially useful when production data include nonlinear interactions among age, temperature, mortality, flow conditions, and culture duration that are difficult to capture with classical regression alone.

Empirical studies now show that machine learning can achieve strong predictive performance across different aquaculture settings, although its success depends on data quality and generalizability. In land-based abalone culture, an ensemble of random forest, gradient boosting, support vector machine, and neural network models predicted weight increase well and identified stable warm temperature and animal age as important growth determinants. In open-sea fish farming, transformer-based models trained on Monte Carlo-expanded datasets parameterized by IoT and weather observations achieved low prediction errors for weight and growth rate, but their performance still depended on reliable input distributions and robustness across different farming environments (Lan et al., 2025).

4 Computational Analysis of Feeding Efficiency and Nutrient Utilization

4.1 Modeling feed intake and feed conversion efficiency

Computational analysis of feeding efficiency in aquaculture begins with accurate estimation of feed intake, because intake directly shapes growth, feed conversion, and waste output. Mathematical and data-driven models are now central to this task, especially because overfeeding increases economic loss and effluent release, whereas underfeeding suppresses growth and reduces production efficiency. At the same time, conventional feed conversion ratio (FCR) remains useful but incomplete, because it measures feed input relative to biomass gain without accounting for feed composition, edible yield, or the nutritional quality of harvested product.

Recent modeling approaches increasingly combine biological realism with predictive accuracy. Mechanistic and nutrient-based frameworks can simulate fish growth, composition, and nutrient utilization under varying feeding levels, feed composition, and environmental conditions, making them useful as decision-support tools for precision farming (Soares et al., 2023). In parallel, newer nutritional bioenergetic models based on dynamic energy budget theory explicitly incorporate digestion and macronutrient composition, allowing prediction not only of weight gain but also of oxygen consumption, ammonia production, and waste outputs under different feeding schedules (Stavrakidis-Zachou et al., 2025).

4.2 Nutritional factors affecting feeding performance

Nutritional factors affect feeding performance through both requirement matching and physiological regulation. Precision nutrition frameworks argue that optimal feeding cannot be defined only by feed amount, because nutrient supply must also align with genetic background, metabolism, environmental conditions, and production goals to minimize waste while sustaining performance (Zhang et al., 2020). Likewise, feed efficiency depends on meeting qualitative and quantitative nutrient requirements simultaneously, while digestibility remains a key determinant because better nutrient digestibility generally improves FCR and nutrient utilization (Hancz, 2020).

Feed composition also influences performance by altering intake regulation, health status, and metabolic use of nutrients. Adequate nutrition is necessary not only to prevent deficiency but also to maintain health and productive performance, and strategic supplementation above minimum requirement for selected amino acids, fatty acids, vitamins, or minerals can improve disease resistance and functional status. More recent work further shows that intake regulation in fish reflects coordinated behavioral and physiological control, and that feed intake is shaped not only by nutrients themselves but also by ingredient inclusion, environmental stressors, ontogeny, and other biological factors that must be represented in advanced predictive models (Soengas et al., 2024).

4.3 Intelligent feeding strategies based on computational prediction

Intelligent feeding strategies increasingly rely on sensors, machine vision, and machine learning to translate fish behavior and environmental data into real-time feeding decisions. Review evidence shows that intelligent feeding control can automatically determine feeding demand by integrating mathematical models, acoustic methods, and computer vision, although practical deployment still depends on improvements in accuracy and robustness under farm conditions. This transition is important because fixed-time or fixed-quantity feeding often fails to reflect dynamic appetite, creating avoidable risks of overfeeding, underfeeding, and water quality deterioration (Zhang et al., 2023).

Applied studies demonstrate that computational prediction can improve feeding precision and production outcomes. A near-infrared computer vision system coupled with a neuro-fuzzy model achieved 98% feeding-decision accuracy and reduced FCR by 10.77% relative to feeding-table management, while also lowering water pollution. More advanced predictive systems have expanded this logic by using optimized neural networks, support vector machines, and dynamic control architectures to infer biomass, uneaten pellets, and feeding endpoints, thereby enabling adaptive rationing in fish and shrimp culture and supporting more efficient smart aquaculture operations (Chen et al., 2022; Wang et al., 2022).

5 Integration of Environmental, Nutritional, and Biological Data for Predictive Aquaculture

5.1 Multivariate analysis of factors affecting aquaculture production

Aquaculture production is governed by interacting environmental, nutritional, and biological variables, so predictive analysis requires multivariate rather than single-factor evaluation. In intensive production systems, growth, survival, feed conversion, and health are simultaneously influenced by stocking density, feeding rate, water temperature, dissolved oxygen, pH, ammonia, nitrite, and tank system conditions, which makes isolated interpretation inadequate for management (El-Hack et al., 2022). This same logic is reflected in recirculating systems, where principal component analysis has been used to convert many correlated water-quality variables into a smaller set of interpretable components that reveal internal data structure and support early prediction of critical events (Silva et al., 2021).

The value of multivariate analysis lies not only in dimensionality reduction but also in discriminating among production environments with different ecological signatures. Comparative pond studies using discriminant analysis showed that fourteen physicochemical variables could clearly separate intensive and less intensive production systems, with dissolved oxygen, temperature, nutrient-related variables, and solids contributing most strongly to classification accuracy (Figure 1) (Delgado-Villafuerte et al., 2026). At the same time, endocrine evidence indicates that growth itself is biologically multicausal, because GH and IGF-I expression responds jointly to diet, temperature, photoperiod, salinity, pollutants, and stocking density, linking external farm conditions with internal physiological regulation.

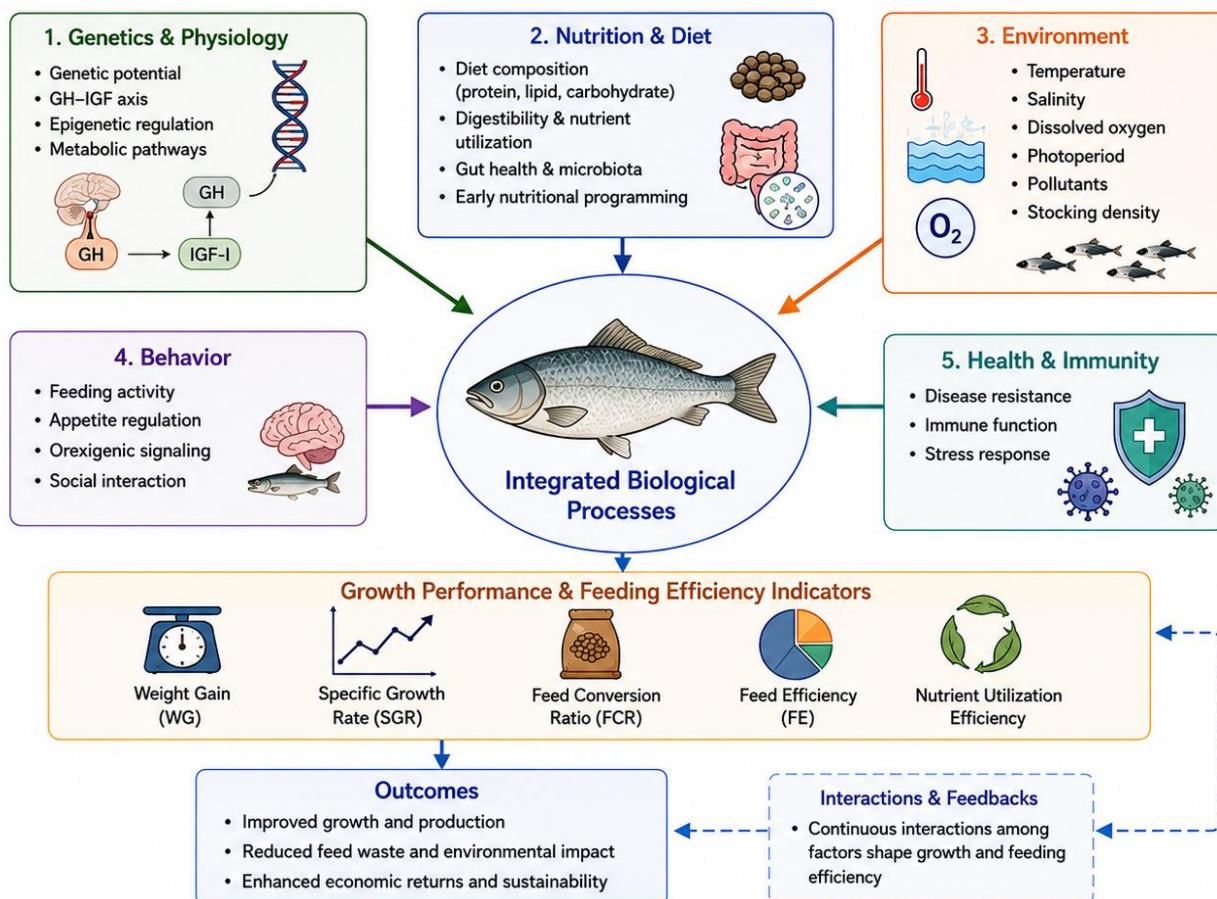


Figure 1 Aquaculture growth performance and feeding efficiency: key biological and environmental determinants

5.2 Digital twin and simulation approaches in aquaculture management

Digital twin approaches extend multivariate analysis by coupling real-time data streams with mechanistic or hybrid models that reproduce the behavior of aquaculture systems in virtual form. In aquaculture, this technology is still at an early stage, but it is increasingly viewed as a solution to the industry's difficulty in observing underwater biological and physical processes continuously and safely. Land-based case studies further show that digital twins under the Precision Fish Farming framework can integrate sensors, IoT infrastructure, and predictive mathematical models to support feeding control, oxygen management, and fish population management in real time.

The main management value of digital twins is that they enable simulation of present and future scenarios rather than passive monitoring alone. Review evidence shows that digital twin systems can support predictive analytics for risk mitigation, feeding optimization, and system-performance improvement, although interoperability and data handling remain major challenges (Huang and Khabusi, 2025). More specialized frameworks such as FishMet demonstrate how a digital twin can incorporate appetite, feeding decisions, feed intake, energetics, and growth into a modular computational service, allowing autonomous model execution and integration with broader farm management platforms.

5.3 Artificial intelligence-driven precision aquaculture systems

Artificial intelligence-driven precision aquaculture systems use integrated sensor and production data to automate monitoring, prediction, and decision-making across feeding, health, and environmental control. Recent reviews describe AI as a transformative force in aquaculture because it improves production efficiency and environmental sustainability through predictive analytics, optimized feeding protocols, and better biomass output, while also exposing persistent barriers in data quality and system integration (Yang et al., 2025). A parallel review focused on AIoT shows that continuous sensing of temperature, pH, dissolved oxygen, salinity, and fish behavior allows AI models to generate real-time insights for water-quality management, species monitoring, and feeding optimization (Huang and Khabusi, 2025).

The most advanced precision aquaculture systems are now moving beyond standalone prediction toward coordinated digital ecosystems that combine AI, IoT, edge computing, and digital twins. Current reviews indicate that machine learning, deep learning, hybrid algorithms, federated learning, and explainable AI are being used to improve predictive control in dynamic aquaculture environments, while digital twins are increasingly framed as the simulation layer that links these tools into proactive management systems (Ratan et al., 2026). At the same time, broader sustainability analyses emphasize that the transition from empirical management to data-driven operations will depend on overcoming sensor reliability problems, data heterogeneity, and the digital divide between high-tech and resource-constrained farms.

6 Case Study: Computational Prediction of Growth Performance and Feeding Efficiency in Pacific White Shrimp (*Litopenaeus vannamei*)

6.1 Experimental design and data collection

Computational prediction in Pacific white shrimp is typically built on production datasets that link growth records with operational and environmental measurements collected across real farming cycles. Industrial and farm-scale studies show that these datasets can include pond-level growth observations, culture duration, stocking density, cumulative feed, and water-quality indicators, and can span either controlled experimental campaigns or multi-year farm operations with thousands of cleaned records (Mujahid et al., 2025). This is important because shrimp body weight prediction is directly relevant to harvest timing, feed management, and stocking decisions, so the design of the dataset determines both model accuracy and management value (Mujahid et al., 2025; Chen et al., 2022).

Experimental design in this species also varies substantially by production system, which affects both the structure and interpretability of the collected data. Controlled recirculating and biofloc studies have used replicated tanks or ponds with specified stocking densities, commercial diets, fixed feeding frequencies, and routine monitoring of temperature, dissolved oxygen, salinity, pH, ammonia, and nitrite, while final biomass, weight gain, survival, and feed conversion ratio are measured as core response variables. In feeding-frequency experiments, data resolution becomes even finer because shrimp are weighed repeatedly during the trial and daily feed inputs are recorded for later calculation of growth, yield, cost, and feed conversion, making these designs particularly suitable for computational feeding analysis (Figure 2) (Liang et al., 2025).

6.2 Computational modeling and prediction analysis

Modeling approaches for *L. vannamei* growth range from empirical growth equations to machine-learning systems and mechanistic feed-conversion models. A Bayesian hierarchical comparison of six nonlinear growth equations found that the Weibull model performed best overall and achieved validation accuracies of 95.76% at pond level and 85.71% at production-cycle level, showing that hierarchical correction can reduce bias from incomplete farm data (Zarzar et al., 2023). Complementing this, growth-trajectory analysis across 15 commercial datasets identified two distinct growth stanzas separated at about 7.5 g, and adapted thermal-unit growth coefficients fit the data better than traditional TGC or SGR formulations.

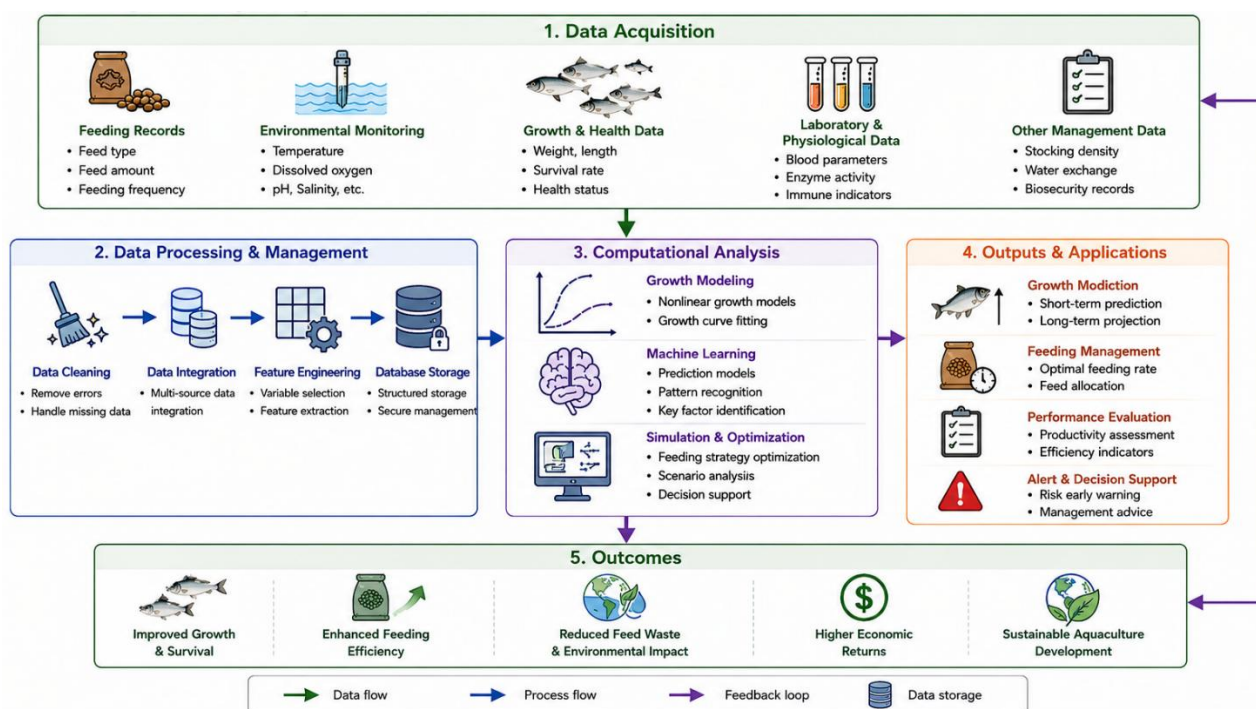


Figure 2 Computational analysis framework for growth performance and feeding efficiency in aquaculture species

Machine-learning studies show that predictive performance improves when models incorporate management and sensor variables rather than relying on water quality alone. In recirculating shrimp culture, support vector machines outperformed multiple linear regression and artificial neural networks for biomass prediction, reaching 90.91% accuracy and enabling real-time feeding decisions from sensor inputs (Chen et al., 2022). In industrial outdoor production, a weighted ensemble reached $R^2 = 0.829$, while SHAP analysis showed that days of culture, stocking density, and cumulative feed contributed more strongly to body-weight prediction than temperature, pH, or dissolved oxygen in a well-managed system (Mujahid et al., 2025).

6.3 Application of computational results in feeding management

The practical value of computational prediction lies in converting growth forecasts into feeding strategies that improve production efficiency without excessive feed waste. Mechanistic modeling has shown that shrimp growth prediction can be linked directly to feed consumption, ammonia excretion, and oxygen demand, creating a basis for stage-specific adjustment of dissolved oxygen supply and feed availability. This management logic is consistent with nutrient-budget evidence from intensive ponds showing that poor feed management raises environmental loading, and that improving feed conversion from 2.0 to 1.8 could reduce total feed use by 147 kg and save \$1027 per crop (Chaikaew et al., 2019).

Computational outputs are also valuable when they identify operational optima rather than simply maximizing feed input. In high-density biofloc culture, growth increased as feed rates approached the standard ration, but feed conversion worsened beyond an inflection point near 101% of the standard feeding rate, indicating that maximum biomass gain and maximum nutrient efficiency are not the same target (Weldon et al., 2021). Similarly, automatic-feeding studies found that moderate feeding frequencies were most effective: quadratic regression identified an optimum near 7.83 feedings per day, and the A8 treatment produced the highest profitability, supporting the use of predictive systems to balance growth, feed utilization, and economic return (Liang et al., 2025).

7 Challenges and Future Perspectives of Computational Aquaculture Analysis

7.1 Limitations of current computational models

Current computational models in aquaculture are limited first by the quality, quantity, and representativeness of available data. Reviews of AI applications consistently identify restricted access to representative datasets, environmental variability, and data-quality maintenance as central obstacles to robust model development and

deployment, especially when models are expected to operate across different farms and culture systems. Deep-learning models face an additional bottleneck because they often require large labeled datasets that are difficult to obtain in aquatic environments, where turbidity, occlusion, and biofouling reduce image quality and complicate annotation (Rather et al., 2024).

A second limitation is that many current models remain difficult to generalize, scale, or interpret in real production settings. Recent reviews note that traditional machine-learning approaches show limited semantic understanding and insufficient scalability in high-dimensional environments, while deep-learning systems still struggle with real-time performance, cross-domain adaptability, and robustness under changing field conditions (Wu et al., 2025). These technical issues are compounded by practical barriers such as high setup costs, computational demands, and the risk of over-automation in systems that still require human observation and judgment, particularly in small or resource-constrained farms (Ratan et al., 2026).

7.2 Future development of ai and data-driven aquaculture technologies

Future development in computational aquaculture is moving toward more integrated and adaptive digital systems rather than isolated prediction models. Emerging reviews emphasize multimodal data fusion, lightweight and edge-deployable models, synthetic data generation, and digital twin-based virtual farming platforms as key next steps for improving model adaptability and operational use (Wu et al., 2025; Ratan et al., 2026). In parallel, integrated frameworks that combine IoT sensing, AI analytics, and blockchain-supported traceability are being positioned as a pathway toward more resilient, transparent, and scalable aquaculture data infrastructures.

The next generation of systems is also likely to depend on distributed and resource-aware computing architectures that can work beyond high-bandwidth commercial farms. Edge-cloud and federated-learning approaches are being developed to reduce latency, protect farm-level data privacy, and enable local processing for real-time monitoring and growth estimation without continuous cloud dependence (Cheng et al., 2022). At the same time, IoT-ML platforms designed for constrained environments suggest that low-cost sensing, local processing, and more efficient training pipelines can make predictive aquaculture more accessible in rural settings rather than restricting advanced analytics to technologically intensive operations (Baena-Navarro et al., 2025).

7.3 Potential contributions to sustainable aquaculture development

The main long-term contribution of computational aquaculture is its potential to improve sustainability by increasing production efficiency while reducing waste and environmental pressure. Reviews of sustainable aquaculture technologies consistently report that AI-supported feeding, growth prediction, and environmental monitoring can reduce human intervention, improve resource utilization, and strengthen traceability and production control across the aquaculture value chain (Yang et al., 2025). These gains matter because improved production efficiency is already recognized as a core pathway toward lower carbon footprint, better feed management, and more sustainable intensive aquaculture systems.

Computational systems may also contribute to sustainability through more proactive management of water quality, pollution, and system resilience. Integrated IoT and machine-learning monitoring has been associated with substantial reductions in losses from water-quality problems and can support survival above 90% under tropical production conditions, showing the practical value of continuous predictive control (Baena-Navarro et al., 2025). Beyond production efficiency alone, AI-enabled precision feeding and effluent-treatment frameworks are increasingly framed as tools for pollution reduction and green fisheries development, provided that implementation economics and system-coupling challenges are addressed.

8. Conclusions

A major advance in computational aquaculture is the shift from descriptive monitoring to integrated prediction of growth, feeding, health, and environmental conditions. Recent reviews show that deep learning and broader AI methods now support growth prediction, intelligent feeding, water-quality forecasting, biomass estimation, and behavioral analysis within the same digital framework, which marks a clear expansion beyond single-purpose

models. This transition is important because computational systems are increasingly expected not only to describe farm status but also to generate predictive, real-time decision support for more efficient and sustainable production.

A second advance is the growing use of hybrid computational architectures that combine sensing, simulation, and machine learning to improve prediction under dynamic farming conditions. AIoT reviews now identify smart feeding, biomass estimation, growth estimation, automation, and water-quality management as core application domains, while newer studies highlight digital twins, federated learning, and other next-generation tools for predictive control and process optimization. Together, these developments show that aquaculture analytics is moving toward connected, adaptive systems rather than isolated statistical models, with increasing emphasis on scalability and resilience across diverse environments.

In production management, the strongest practical applications are in feeding control, water-quality monitoring, and autonomous farm supervision. Smart aquaculture systems can now integrate real-time sensing with predictive models so that fishpond conditions are monitored remotely, growth can be forecast from multiple system parameters, and autonomous feeding can reduce leftover feed. Reinforcement-learning control in recirculating aquaculture extends this further by optimizing feeding rates together with water-quality management, improving tracking accuracy, reducing feed consumption, and increasing long-term system stability compared with conventional control methods.

Commercial and field-oriented reviews also indicate that AI-based management delivers measurable operational benefits when deployed at farm scale. Reported applications include automated and adaptive feeding schedules, early disease detection, biomass estimation, and predictive resource management, with commercial systems showing feed-cost reductions, lower mortality, and improved compliance with environmental standards. More broadly, AI-assisted farm management improves resource efficiency, reduces labor demands, and supports better decisions on fish health, nutrition, and product quality, which makes computational tools increasingly relevant to everyday aquaculture operations rather than only experimental settings (Ragab et al., 2024).

Future research should focus on making computational aquaculture models more transferable, data-efficient, and interoperable across species and production systems. The most consistent priorities are multimodal data fusion, edge computing, lightweight model design, synthetic data generation, and digital twin-based virtual farming, all of which aim to address persistent problems in real-time performance, generalization, and limited labeled datasets. Other reviews reach the same conclusion from a deployment perspective, arguing that broader geographic datasets, standardized data-collection protocols, and integrated AI frameworks are necessary if predictive systems are to become more robust and comparable across studies and farms.

A second priority is ensuring that future innovation remains economically and socially deployable, not only technically advanced. Several recent reviews emphasize that high implementation costs, infrastructure gaps, regulatory constraints, and the digital divide still limit adoption, especially in small-scale and resource-constrained settings. Accordingly, the most promising direction is the development of scalable, adaptive, and standardized AI systems that combine IoT, edge intelligence, blockchain, or robotics where useful, while remaining practical enough to support sustainable aquaculture growth and global seafood security.

References

- Baena-Navarro R., Carriazo-Regino Y., Torres-Hoyos F., and Pinedo-López J., 2025, Intelligent prediction and continuous monitoring of water quality in aquaculture: Integration of machine learning and Internet of Things for sustainable management, *Water*, 17(1): 82.
<https://doi.org/10.3390/w17010082>
- Chen F., Sun M., Du Y., Xu J., Zhou L., Qiu T., and Sun J., 2022, Intelligent feeding technique based on predicting shrimp growth in recirculating aquaculture system, *Aquaculture Research*, 53(12): 4401-4413.
<https://doi.org/10.1111/are.15938>
- Delgado-Villafuerte C. R., González-Martínez A., Peñarrieta-Macias F., Barba C., and García A., 2026, Multivariate water quality patterns as a proxy for environmental performance in tropical pond-based aquaculture systems, *Sustainability*, 18(7): 3309.
<https://doi.org/10.3390/su18073309>

- El-Hack M.A.A., El-Saadony M., Nader M.M., Salem H., El-Tahan A.M., Soliman S.M.A., and Khafaga A., 2022, Effect of environmental factors on growth performance of Nile tilapia (*Oreochromis niloticus*), International Journal of Biometeorology, 66(11): 2183-2194.
<https://doi.org/10.1007/s00484-022-02347-6>
- Hu J., Yin J., Yang C.-T., Zhou Y., and Li C., 2025, Intelligent forecasting model for aquatic production based on artificial neural network, Frontiers in Marine Science, 12: 1556294.
<https://doi.org/10.3389/fmars.2025.1556294>
- Huang H., Pan X., Yang J., Guo Z., and Shen Y., 2025, An intelligent feeding method for recirculating aquaculture systems based on visual perception and large language models, 2025 IEEE International Conference on Big Data (BigData), 2025: 3565-3572.
<https://doi.org/10.1109/BigData66926.2025.11401056>
- Hancz C., 2020, Feed efficiency, nutrient sensing and feeding stimulation in aquaculture: A review, Acta Agraria Kaposváriensis, 24(1): 35-54.
<https://doi.org/10.31914/aak.2375>
- Lan H.-Y., Ubiña N., Zhang K.-X., Cheng S.-C., and Li S.-Y., 2025, Fusion of transformer-based deep learning and Monte-Carlo fish growth simulation for aquaculture smart transformation, Engineering Computations, 43(7): 2916-2931.
<https://doi.org/10.1108/EC-07-2024-0599>
- Li H., Cui Z., Cui H., Bai Y., Yin Z., and Qu K., 2023, A review of influencing factors on a recirculating aquaculture system: Environmental conditions, feeding strategies, and disinfection methods, Journal of the World Aquaculture Society, 54(3): 566-602.
<https://doi.org/10.1111/jwas.12976>
- Liang Q., Liu G., Luan Y., Niu J., Li Y., Chen H., Liu Y., and Zhu S., 2025, Impact of feeding frequency on growth performance and antioxidant capacity of *Litopenaeus vannamei* in recirculating aquaculture systems, Animals, 15(2): 192.
<https://doi.org/10.3390/ani15020192>
- Mujahid M. A. A. A., Azizah F. F. N., Indrayana G. G., Rachminiwati N., Sakai Y., and Yagi N., 2025, Prediction of shrimp growth by machine learning: The use of actual data of industrial-scale outdoor white shrimp (*Litopenaeus vannamei*) aquaculture in Indonesia, Aquaculture Journal, 5(4): 27.
<https://doi.org/10.3390/aquacj5040027>
- Naylor R., Hardy R., Buschmann A., Bush S., Cao L., Klinger D. H., Little D., Lubchenco J., Shumway S., and Troell M., 2021, A 20-year retrospective review of global aquaculture, Nature, 559(17851): 551-563.
<https://doi.org/10.1038/s41586-021-03308-6>
- Nazmi H., Siau N.Z., Bramantoro A., and Suhaili W.S., 2023, Predictive modeling of marine fish production in Brunei Darussalam's aquaculture sector: A comparative analysis of machine learning and statistical techniques, International Journal of Advanced and Applied Sciences, 10(7): 109-126.
<https://doi.org/10.21833/ijaas.2023.07.013>
- Rahman L.F., Marufuzzaman M., Alam L., Bari M.A., Sumaila U.R., and Sidek L., 2021, Developing an ensemble machine learning prediction model for marine fish and aquaculture production, Sustainability, 13(16): 9124.
<https://doi.org/10.3390/su13169124>
- Ratan R., Ashwini M., Kamilya D., and Nagarajan V., 2026, Artificial intelligence and digital innovations in precision aquaculture: Advancements, applications, and future directions, Franklin Open, 2026: 100567.
<https://doi.org/10.1016/j.fraope.2026.100567>
- Rather M.A., Ahmad I., Shah A., Hajam Y.A., Amin A., Khursheed S., Ahmad I., and Rasool S., 2024, Exploring opportunities of artificial intelligence in aquaculture to meet increasing food demand, Food Chemistry: X, 22: 101309.
<https://doi.org/10.1016/j.fochx.2024.101309>
- Șerban D., Barbacariu C. A., Ivancia M., and Creangă Ș., 2025, Molecular regulation of growth in aquaculture: From genes to sustainable production, Life, 15(12): 1831.
<https://doi.org/10.3390/life15121831>
- Silva L. C. B., Lopes B., Pontes M., Blanquet I., Segatto M., and Marques C., 2021, Fast decision-making tool for monitoring recirculation aquaculture systems based on a multivariate statistical analysis, Aquaculture, 530: 735931.
<https://doi.org/10.1016/j.aquaculture.2020.735931>
- Soares F., Nobre A., Raposo A., Mendes R., Engrola S., Rema P., Conceição L., and Silva T., 2023, Development and application of a mechanistic nutrient-based model for precision fish farming, Journal of Marine Science and Engineering, 11(3): 472.
<https://doi.org/10.3390/jmse11030472>
- Soengas J., Comesaña S., Blanco A., and Conde-Sieira M., 2024, Feed intake regulation in fish: Implications for aquaculture, Reviews in Fisheries Science and Aquaculture, 33(1): 8-60.
<https://doi.org/10.1080/23308249.2024.2374259>
- Stavrakidis-Zachou O., Eding E., Papandroulakis N., and Lika K., 2025, A nutritional bioenergetic model for farmed fish: Effects of food composition on growth, oxygen consumption and waste production, Aquaculture Nutrition, 2025(1): 9010939.
<https://doi.org/10.1155/anu/9010939>
- Takahashi Y. and Komeyama K., 2023, Development of a feeding simulation to evaluate how feeding distribution in aquaculture affects individual differences in growth based on the fish schooling behavioral model, PLoS ONE, 18(2): e0280017.
<https://doi.org/10.1371/journal.pone.0280017>

- Takahashi Y., Yoshida T., Yamazaki Y., Takahashi E., Yamaha E., and Komeyama K., 2026, An aquaculture simulator for rainbow trout (*Oncorhynchus mykiss*) based on a fish schooling behavioral model and a dynamic energy budget, Scientific Reports, 16(1): 7706.
<https://doi.org/10.1038/s41598-026-39028-y>
- Weldon A., Davis D., Rhodes M., Reis J., Stites W., and Ito P., 2021, Feed management of *Litopenaeus vannamei* in a high density biofloc system, Aquaculture, 544: 737074.
<https://doi.org/10.1016/j.aquaculture.2021.737074>
- Wu A.-Q., Li K., Song Z., Lou X., Hu P., Yang W., and Wang R.-F., 2025, Deep learning for sustainable aquaculture: Opportunities and challenges, Sustainability, 17(11): 5084.
<https://doi.org/10.3390/su17115084>
- Yang H., Feng Q., Xia S., Wu Z., and Zhang Y., 2025, AI-driven aquaculture: A review of technological innovations and their sustainable impacts, Artificial Intelligence in Agriculture, 15(3): 508-525.
<https://doi.org/10.1016/j.aiia.2025.01.012>
- Young T., Laroche O., Walker S., Miller M. R., Casanovas P., Steiner K., Esmaili N., Zhao R., Bowman J., Wilson R., Bridle A., Carter C., Nowak B., Alfaro A., and Symonds J., 2023, Prediction of feed efficiency and performance-based traits in fish via integration of multiple omics and clinical covariates, Biology, 12(8): 1135.
<https://doi.org/10.3390/biology12081135>
- Zarzar C. A., Fernandes T. J., and Oliveira I. R. C. D., 2023, Modeling the growth of Pacific white shrimp (*Litopenaeus vannamei*) using the new Bayesian hierarchical approach based on correcting bias caused by incomplete or limited data, Ecological Informatics, 77: 102271.
<https://doi.org/10.1016/j.ecoinf.2023.102271>
- Zhang Y., Lu R., Qin C., and Nie G., 2020, Precision nutritional regulation and aquaculture, Aquaculture Reports, 18: 100496.
<https://doi.org/10.1016/j.aqrep.2020.100496>



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Research Insight

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Statistical Analysis of Environmental Effects on Shrimp Growth and Survival Rate

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Abstract Shrimp aquaculture is highly dependent on environmental stability, and fluctuations in water quality parameters can significantly affect growth performance, physiological health, and survival rates. This review aims to summarize the application of statistical approaches for evaluating environmental effects on shrimp production and to establish a quantitative framework for understanding environmental-growth-survival relationships. Key environmental factors, including temperature, dissolved oxygen, salinity, pH, ammonia, and nitrite, are discussed in relation to their impacts on shrimp metabolism, immune responses, feeding behavior, and mortality risk. Statistical methods such as correlation analysis, regression models, mixed-effects models, survival analysis, and machine learning algorithms are evaluated for their effectiveness in identifying critical environmental drivers and predicting shrimp performance. A case study based on Pacific white shrimp (*Litopenaeus vannamei*) production demonstrates how environmental monitoring data can be integrated with predictive models to determine optimal culture conditions and develop early-warning systems. Furthermore, the integration of statistical modeling with sensor-based monitoring and precision aquaculture technologies provides new opportunities for improving production efficiency and environmental management. Overall, statistical analysis serves as an essential tool for transforming environmental data into actionable strategies, supporting sustainable shrimp farming under increasing environmental variability and climate-related challenges.

Keywords Shrimp aquaculture; Environmental factors; Statistical modeling; Growth performance; Survival analysis

1 Introduction

Shrimp aquaculture has become one of the most economically significant segments of global aquaculture, driven by strong international demand, high market value, and sustained production growth over recent decades. Farmed shrimp reached 6 million tonnes in 2018, and production growth from 1998 to 2018 exceeded that of global aquaculture overall, underscoring the sector's importance to export earnings, rural livelihoods, and broader aquatic food systems. At the same time, shrimp farming remains vulnerable to major sustainability constraints, especially disease, climate variability, and the resource intensity of intensive production systems. These pressures make productivity improvement not simply a matter of increasing inputs, but of understanding how culture conditions shape biological performance under commercial farming conditions. For this reason, research on shrimp growth and survival has become central to aquaculture development, because these two outcomes directly affect yield, profitability, and farm resilience in a sector expected to continue expanding despite environmental uncertainty.

Among the many determinants of shrimp production, environmental conditions are consistently identified as major influences on growth, survival, and final yield. Temperature is especially important because it regulates feeding activity, metabolism, and growth rate, while excessive or prolonged exposure to unfavorable temperature ranges can impair production and increase mortality risk. Experimental work on juvenile *Penaeus vannamei* further showed that the best survival occurred between 20°C and 30°C at salinities above 20‰, whereas the best growth was observed between 25°C and 35°C, with overall production optimized near 28°C-30°C and salinities of 33‰-40‰. In pond systems, dissolved oxygen, pH, alkalinity, calcium hardness, and nitrogen-related variables also affect physiological stress and performance, even when measured values are not immediately lethal. This means that shrimp response to the culture environment depends not only on single variables in isolation, but on how multiple water-quality factors fluctuate through time and interact with stocking and management conditions.

Evidence from commercial and pond-based studies shows that environmental variability can explain meaningful differences in shrimp performance among ponds exposed to otherwise similar production regimes. In semi-intensive *Litopenaeus vannamei* farming, temperature and dissolved oxygen showed significant variation among ponds and were associated with production outcomes, while sensitivity analysis indicated that dissolved oxygen variability affected final production more than the other variables considered (Ruiz-Velazco et al., 2022). In inland low-salinity ponds, wide temporal and spatial variation in water quality was also documented, and survival and production were positively correlated with alkalinity and calcium hardness, suggesting that suboptimal but nonlethal conditions can still reduce performance through chronic stress pathways. Environmental effects also extend beyond growth alone, because changes in temperature, salinity, oxygenation, and pH can increase physiological stress and disease susceptibility, particularly in intensive pond systems where animals are reared at high densities. Accordingly, growth and survival should be treated as integrative indicators of the cumulative environmental quality experienced during the production cycle.

Given this complexity, statistical analysis provides an essential framework for identifying which environmental factors are most strongly associated with shrimp growth and survival and for translating farm observations into decision-relevant evidence. Regression-based approaches have already been used to relate water temperature, salinity, dissolved oxygen, stocking density, pond size, cultivation duration, and feed inputs to final weight and survival in commercial farms, showing how quantitative models can support production improvement (Ruiz-Velazco et al., 2022). More advanced predictive approaches, such as artificial neural networks, have also outperformed conventional regression forms under complex commercial conditions, indicating that shrimp growth patterns may reflect nonlinear and interacting effects that simple models do not always capture fully. Against this background, the present study aims to statistically evaluate the environmental effects on shrimp growth and survival rate by examining key water-quality and production variables, quantifying their relationships with biological outcomes, and establishing an analytical framework that can help improve interpretation, prediction, and management in shrimp aquaculture.

2 Environmental Variables and Their Biological Effects on Shrimp Performance

2.1 Water temperature effects

Water temperature is a primary environmental determinant of shrimp metabolism, feeding, and growth because it directly regulates physiological process rates in ectothermic animals. In *Litopenaeus vannamei*, higher temperatures generally increase metabolic activity and feeding, but performance declines once thermal conditions move beyond the optimal range or remain unfavorable for extended periods. Experimental evidence further shows that growth response is size-dependent: smaller shrimp can tolerate and benefit from slightly higher temperatures, whereas larger shrimp perform better at lower thermal optima, indicating that temperature management should account for developmental stage as well as mean pond conditions.

Controlled studies converge on an optimal production window centered near 25°C–30°C, although exact values vary with salinity, shrimp size, and culture system. Juvenile white shrimp showed best combined growth and survival around 28°C–30°C and moderate-to-high salinity, while thermal acclimation work also identified 25°C–30°C as the most effective range for production based on standard metabolic performance. By contrast, exposure to excessively warm conditions can suppress performance: pond observations found impaired production when shrimp experienced more hours above 33°C, and nursery trials reported survival declines as temperature increased from 28°C to 32°C.

2.2 Water quality parameters

Shrimp survival and physiological stability depend not only on temperature but also on dissolved oxygen, pH, salinity, alkalinity, hardness, and nitrogenous wastes. In commercial and pond systems, these variables often remain below lethal thresholds yet still move outside optimal ranges often enough to impose chronic stress, which can reduce survival and productivity without causing immediate mortality. Field evidence indicates that dissolved oxygen tends to support growth, while water chemistry linked to buffering and ionic balance, especially alkalinity and calcium hardness, is positively associated with survival and production outcomes (Srinivasan et al., 2025).

Among individual water-quality stressors, ammonia is especially important because it affects both physiology and immunity. Review evidence shows that elevated ammonia inhibits molting-related processes, suppresses phenoloxidase and antimicrobial activity, and weakens innate immune responses, thereby compromising shrimp growth and resilience (Zhao et al., 2020). Mechanistic work in *L. vannamei* gills further demonstrates that ammonia exposure damages gill structure and disrupts redox balance, apoptosis, energy metabolism, and osmoregulation, confirming that poor nitrogen management can destabilize the physiological systems required for survival under culture conditions.

2.3 Environmental interactions

Environmental stress in shrimp ponds rarely results from a single factor acting alone; instead, temperature, salinity, oxygen, pH, and waste-related variables interact over time to shape health and performance. Reviews of shrimp disease ecology emphasize that fluctuations in abiotic conditions increase physiological stress and disease susceptibility, especially in intensive systems with high stocking densities and limited waste removal (Kautsky et al., 2000; Millard et al., 2020). This interaction perspective is important because the biological effects of one variable may depend on the level or rate of change of another, making single-factor interpretations incomplete for real farm environments (Millard et al., 2020).

Experimental studies support this cumulative-stress view by showing that combined stressors impose larger physiological costs than isolated exposures. Under simultaneous high temperature and low pH, Pacific white shrimp increased food intake, oxygen uptake, and ammonia excretion, yet failed to translate that metabolic effort into improved growth, indicating energetic compensation at the expense of production. Likewise, integrated comparisons of ammonia, nitrite, and sulfide stress found tissue injury, altered antioxidant responses, and disrupted immune and metabolic pathways across all treatments, with nitrite producing the most severe overall effects (Han et al., 2025).

3 Data Collection and Statistical Methodology for Environmental Impact Assessment

3.1 Experimental design and environmental monitoring strategies

Environmental impact assessment in shrimp aquaculture depends on a design that captures both pond-level variation and time-dependent changes in water conditions. Farm-based studies have therefore used multiple ponds as observational units and monitored key production outcomes such as growth, survival, and biomass alongside environmental and management variables across an entire production cycle (Ruiz-Velazco et al., 2022). This approach is strengthened when monitoring covers physicochemical variables concurrently with biological performance, because it allows environmental measurements to be directly aligned with shrimp response over time (Nazarudin et al., 2025).

Effective monitoring strategies also depend on sampling frequency and method. Semi-intensive pond studies have measured temperature and dissolved oxygen twice daily while salinity was measured weekly, whereas other culture studies combined in situ multiprobe measurements with ex situ spectrophotometric and titration analyses to cover a broader set of variables including nutrients, alkalinity, and organic matter (Ruiz-Velazco et al., 2022). This mixed monitoring design is useful because some variables fluctuate rapidly and require frequent field measurement, while others are better captured through laboratory-based analyses with higher analytical specificity (Akbarurrasyid et al., 2023).

3.2 Statistical approaches for analyzing environmental-growth relationships

Conventional statistical analysis in shrimp environmental studies usually begins with variance and correlation methods to identify which factors differ among ponds and which variables track biological outcomes. In commercial *Penaeus vannamei* production, analysis of variance was used to test whether environmental conditions differed among ponds, and correlation analysis was then applied to link environmental and management variables with final weight and survival. Similar pond studies used regression analysis specifically to quantify the level of relationship between water-quality parameters and shrimp growth, supporting an empirical basis for variable screening before predictive modeling (Akbarurrasyid et al., 2023).

Regression models remain central when the objective is to estimate environmental-growth relationships quantitatively and test predictive usefulness. Simple linear regression has been used to model production parameters and to run sensitivity simulations, showing how changes in dissolved oxygen, temperature, and management factors could alter final output (Ruiz-Velazco et al., 2022). Other shrimp-environment studies extended linear regression to longer monitoring datasets and multiple life-cycle periods, showing that temperature, salinity, dissolved oxygen, and even meteorological variables can explain part of the variability in shrimp abundance or performance, although explanatory power varies by period and outcome.

3.3 Advanced modeling techniques for prediction and risk assessment

Advanced modeling techniques are increasingly used when environmental effects are nonlinear, high-dimensional, or time dependent. In commercial shrimp growth prediction, artificial neural networks outperformed eight traditional regression forms after training and validation on farm datasets, indicating that flexible models can better capture complex production environments (Yu et al., 2005). More recent machine-learning work using eco-green aquaculture data compared neural networks, support vector regression, decision trees, and random forest models, and identified dissolved oxygen, nitrate, and total *Vibrio* as the most important predictors of daily shrimp growth (Arfiati et al., 2025).

Risk assessment applications have also expanded from growth prediction to environmental alert systems and disease forecasting. Real-time shrimp farm analytics now combine sensors, cloud storage, multivariate regression, and classification algorithms to predict next-day water conditions and categorize production levels, with reported performance of $R^2 = 0.94$ for regression and 97.84% accuracy for random forest classification (Ahmed et al., 2024). At the disease level, machine-learning and deep-learning studies have used physicochemical plus spatial variables to map white spot disease susceptibility and historical environmental time series to forecast outbreak risk, shifting farm management from reactive response toward proactive prevention (Tuyen et al., 2023; Udayakumar et al., 2025).

4 Statistical Evaluation of Environmental Effects on Shrimp Growth Performance

4.1 Relationship between environmental conditions and growth indicators

Statistical evaluation of shrimp growth performance consistently shows that environmental conditions are closely linked to core production indicators such as average body weight, specific growth rate, survival, and biomass yield. In semi-intensive farms, dissolved oxygen showed a strong positive correlation with average body weight, whereas water temperature was negatively correlated with both survival and average daily growth, indicating that even narrow thermal variation can measurably affect performance outcomes (Srinivasan et al., 2025). A separate multivariate analysis using canonical correlation likewise found a significant first canonical root between water quality and shrimp growth, with temperature emerging as the main environmental contributor and specific growth rate dominating the biological response side.

Evidence from pond-scale production studies further suggests that growth indicators respond not only to single variables but to the combined structure of environmental variation across ponds and time. In a commercial farm dataset, final weight was positively related to both temperature and dissolved oxygen, while temperature and dissolved oxygen also showed the greatest between-pond variability, supporting their value as explanatory variables in growth evaluation (Ruiz-Velazco et al., 2022). Daily monitoring in intensive ponds also showed that shrimp growth was strongly influenced by salinity, nitrite, alkalinity, and pH, with estimated contributions of 80.4%, 75.6%, 67.8%, and 55.7%, respectively, demonstrating that statistically relevant growth predictors extend beyond temperature alone.

4.2 Modeling growth responses under different environmental scenarios

Modeling shrimp growth under different environmental scenarios has progressed from conventional regression toward approaches that explicitly accommodate changing pond conditions and nonlinear responses. Linear mixed-effects models have been used to assess how temperature exposure patterns influence shrimp performance while accounting for repeated observations within ponds and yearly clustering, allowing fixed environmental effects and random farm-level variation to be separated statistically. In freshwater intensive culture, a parameterized Gompertz

growth model was used across multiple stocking densities and temperatures, showing that predictive statistical-mathematical modeling can estimate growth trajectories while evaluating the likely effect of external environmental drivers over time (Araneda et al., 2020).

More flexible predictive models appear to perform better when shrimp farms operate under complex and fluctuating environmental conditions. In a commercial dataset, artificial neural networks outperformed eight regression functional forms and produced the most accurate growth predictions, indicating that nonlinear interactions among environmental factors are important in real-world culture systems. More recent machine-learning comparisons in eco-green aquaculture similarly found that growth could be modeled as a function of water-quality variables, and that dissolved oxygen, nitrate, and total *Vibrio* had the highest importance for predicting daily shrimp growth, reinforcing the usefulness of data-driven scenario modeling for environmental assessment (Arfiati et al., 2025).

4.3 Identification of optimal environmental conditions for growth enhancement

Statistical optimization studies indicate that shrimp growth enhancement depends on identifying environmental ranges that maximize growth while avoiding survival loss or water-quality deterioration. Response surface analysis of temperature-salinity interactions in biofloc nursery production found that the optimum conditions for maximizing final weight, specific growth rate, productivity, and survival were a temperature of 27.25°C and salinity of 25.5 g/L, showing the value of multivariable optimization rather than one-factor-at-a-time interpretation (Figure 1). In intensive freshwater culture, predictive growth modeling further showed that the best productivity yield occurred above 26°C, while culture below 22°C was least efficient, supporting the view that optimal thermal conditions are both system-specific and statistically identifiable (Araneda et al., 2020).

Optimization also depends on maintaining environmental variables within acceptable operational ranges through continuous monitoring and classification. Real-time monitoring work identified temperature, pH, dissolved oxygen, salinity, and related indicators as key water-quality variables for production assessment, and machine-learning classification achieved high accuracy in assigning shrimp production levels from these measurements (Ahmed et al., 2024). Complementary pond monitoring showed that dissolved oxygen and pH can fluctuate toward critical thresholds while ammonia and nitrite can rise abruptly, suggesting that optimal growth enhancement requires not only target conditions but also early-warning detection of deviations before they suppress growth performance (Nazarudin et al., 2025).

5 Statistical Analysis of Environmental Effects on Shrimp Survival Rate

5.1 Environmental stress factors associated with shrimp mortality

Shrimp mortality is strongly shaped by environmental stress, particularly when ponds experience unstable temperature, salinity, oxygen, or nitrogenous waste conditions. Evidence from disease-focused reviews shows that abiotic conditions influence shrimp susceptibility to white spot disease, and that stressors in farm settings usually occur simultaneously rather than in isolation, which increases the difficulty of attributing mortality to a single factor (Millard et al., 2020). Experimental studies likewise show that common toxicants in culture water reduce survival directly: ammonia, nitrite, and sulfide all lowered the survival rate of *Litopenaeus vannamei*, with tissue damage increasing as stress concentration rose and nitrite causing the most severe overall damage (Han et al., 2025).

Nitrogen-related stress appears especially important because it compromises both physiology and disease resistance before outright mortality occurs. Elevated ammonia beyond tolerance limits inhibits molting, growth, phenoloxidase activity, and antimicrobial defenses, thereby weakening innate immunity and increasing vulnerability to loss (Zhao et al., 2020). Multi-factor experiments further show that survival declines at higher ammonia-N and nitrite-N concentrations, and that survival rate is most strongly affected by ammonia-N among the tested factors, while interaction effects with temperature can significantly alter biological response (Li et al., 2024).

5.2 Survival analysis and mortality prediction models

Statistical models for shrimp survival increasingly treat mortality as a dynamic response to water quality, disease pressure, and management conditions. Dynamic stock modeling of white spot disease in intensive *L. vannamei*

farms showed that mortality decreased when temperature and dissolved oxygen increased or salinity decreased, while early mortality occurred when temperature increased, oxygen decreased, or ponds were larger. A related dynamic stock analysis for acute hepatopancreatic necrosis disease found that mortality was more severe when salinity was high and pond productivity was low, and that warmer water was associated with earlier outbreaks.

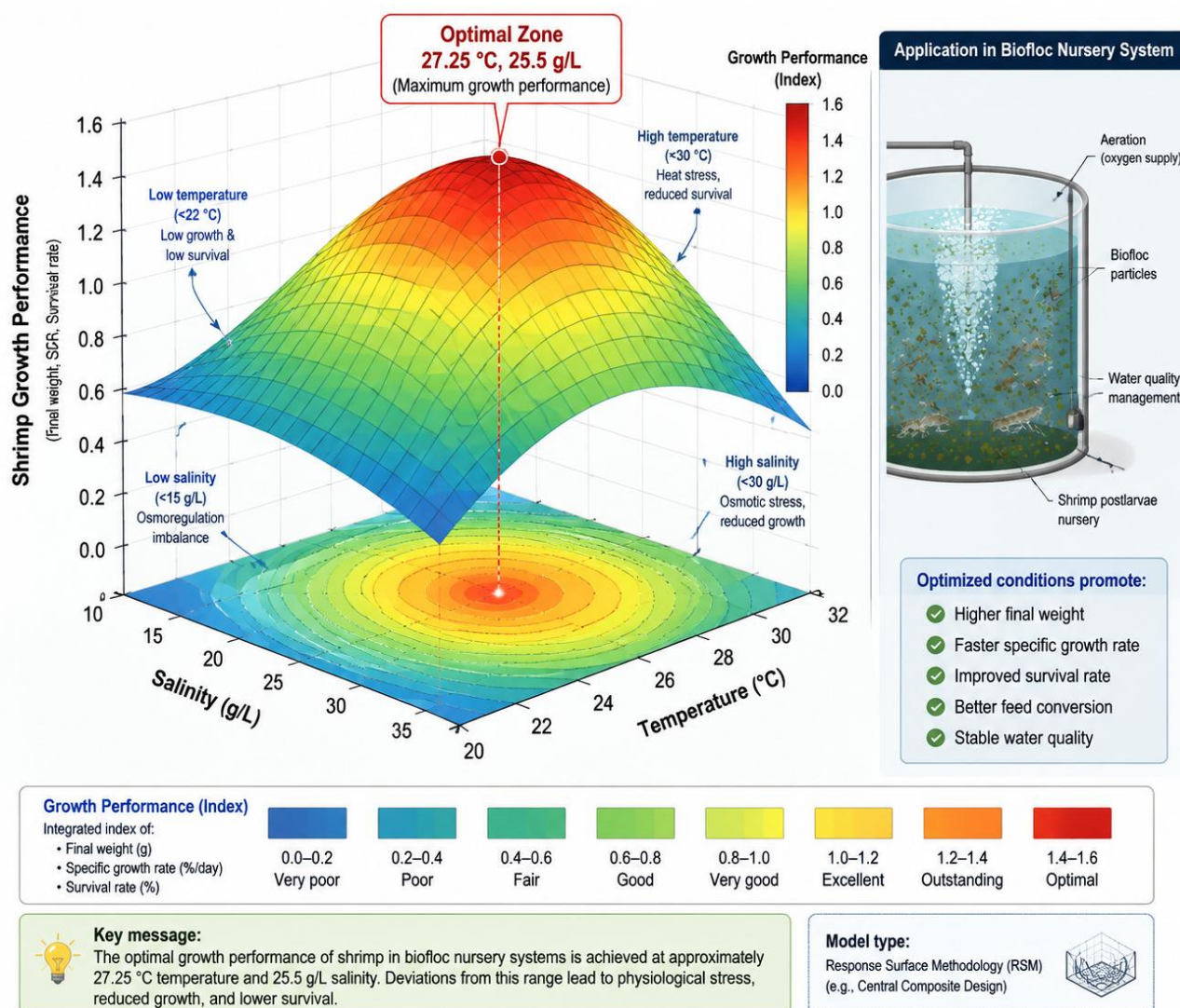


Figure 1 Response surface optimization of shrimp growth performance under different temperature and salinity combinations in intensive nursery systems. The three-dimensional model illustrates the interaction between temperature and salinity and identifies the optimal environmental zone for maximizing growth, productivity, and survival

Machine-learning approaches extend these analyses by predicting survival rate directly from multivariable water-quality data. A Random Forest survival model based on dissolved oxygen, temperature, pH, salinity, and total dissolved solids reported strong fit statistics and identified dissolved oxygen and salinity as the most influential predictors of survival. Logistic regression has also been used at farm scale to estimate the probability of disease occurrence under climatic, operational, and biosecurity conditions, showing that longer crop duration and more years of farm operation increased disease risk, while adaptive management and training reduced it (Le et al., 2024).

5.3 Early-warning systems based on environmental monitoring data

Early-warning systems aim to detect environmental deterioration before it produces mortality, and recent shrimp studies increasingly combine sensors, automation, and predictive analytics for this purpose. IoT-based monitoring systems have been developed to track dissolved oxygen, pH, and temperature continuously and to send real-time alerts when threshold values are exceeded, reducing dependence on manual pond checks. Broader evidence from

aquaculture sensor reviews also indicates that IoT water monitoring improves growth, reduces culture mortality, and enables rapid detection of atypical total ammonia nitrogen levels, although challenges remain in automation and rural deployment (Flores-Iwasaki et al., 2025).

Prediction-based early warning is moving beyond direct sensor readings to infer harder-to-measure risk variables and forecast next-day conditions. Deep learning studies show that sequential measurements of salinity, temperature, pH, and dissolved oxygen can be forecast with LSTM models to provide advance warning of deteriorating water quality (Thai-Nghe et al., 2020). In high-density recirculating shrimp systems, optimized GRNN models predicted ammonia and nitrite from low-cost sensor inputs and were explicitly proposed for integration into IoT platforms to enable real-time water-environment early warning (Chen et al., 2024).

6 Case Study: Statistical Assessment of Environmental Drivers Affecting Pacific White Shrimp (*Litopenaeus vannamei*) Growth and Survival

6.1 Study design and environmental data collection

A robust case-study design for assessing environmental drivers of *Litopenaeus vannamei* growth and survival should combine repeated pond observations with concurrent measurement of biological and physicochemical variables across the culture cycle. Recent semi-intensive pond work monitored temperature, pH, salinity, dissolved oxygen, ammonia, nitrite, nitrate, and trace elements alongside shrimp growth and survival over a 56-day culture period, while commercial farm monitoring in India sampled water quality across four farms during a 90-110 day production window and linked these records to yield, body weight, and survival outcomes (Srinivasan et al., 2025). This type of design is strengthened when environmental observations are synchronized with production metrics, because it allows subsequent analyses to distinguish whether short-term fluctuations or longer-term pond conditions are more strongly associated with shrimp performance (Figure 2) (Nazarudin et al., 2025).

Case studies also benefit from spatially and temporally structured sampling that captures seasonal shifts and pond heterogeneity rather than relying on single end-point measurements. Coastal monitoring studies in intensive shrimp areas sampled before stocking and after harvest across multiple locations, measured surface and bottom water quality, and supplemented pond observations with rainfall and management data, whereas long-term low-salinity farm studies recorded hourly pond temperatures across 22 ponds over four growing seasons and paired them with stocking, survival, and production records (Mustafa et al., 2022). Together, these designs show that environmental assessment is most informative when it integrates high-frequency sensor data, laboratory water analysis, and farm management information within the same analytical framework (Mustafa et al., 2022).

6.2 Statistical modeling of environmental impacts on shrimp production

The statistical core of this case study should begin with methods that identify variation among ponds and then quantify environmental relationships with growth and survival. Semi-intensive production studies have used analysis of variance to test whether environmental conditions differ significantly across ponds, followed by correlation and simple linear regression to relate those conditions to final weight and survival, while broader coastal assessments combined descriptive, multivariate, and non-parametric statistics to evaluate water-quality status under intensive production (Mustafa et al., 2022). These approaches are appropriate for a case study because they first establish whether environmental heterogeneity exists and then estimate which variables contribute most strongly to differences in production outcomes (Ruiz-Velazco et al., 2022).

More advanced modeling can then be used to improve prediction and account for nonlinear or interacting effects. Machine-learning analyses in eco-green systems modeled shrimp growth from 2021–2023 data using multiple regression algorithms and identified dissolved oxygen, nitrate, and total *Vibrio* as the most important predictors of daily growth, while Bayesian hierarchical growth modeling on an industrial farm showed that a Weibull model gave the best overall fit and achieved 95.76% pond-level predictive accuracy despite incomplete or limited farm data (Arfiati et al., 2025). Experimental evidence also shows that single-factor models can miss biologically important interactions, because a four-factor orthogonal design found that survival was most affected by ammonia, growth was most affected by salinity, and the ammonia $\times$ temperature interaction significantly influenced all three growth indices (Li et al., 2024).

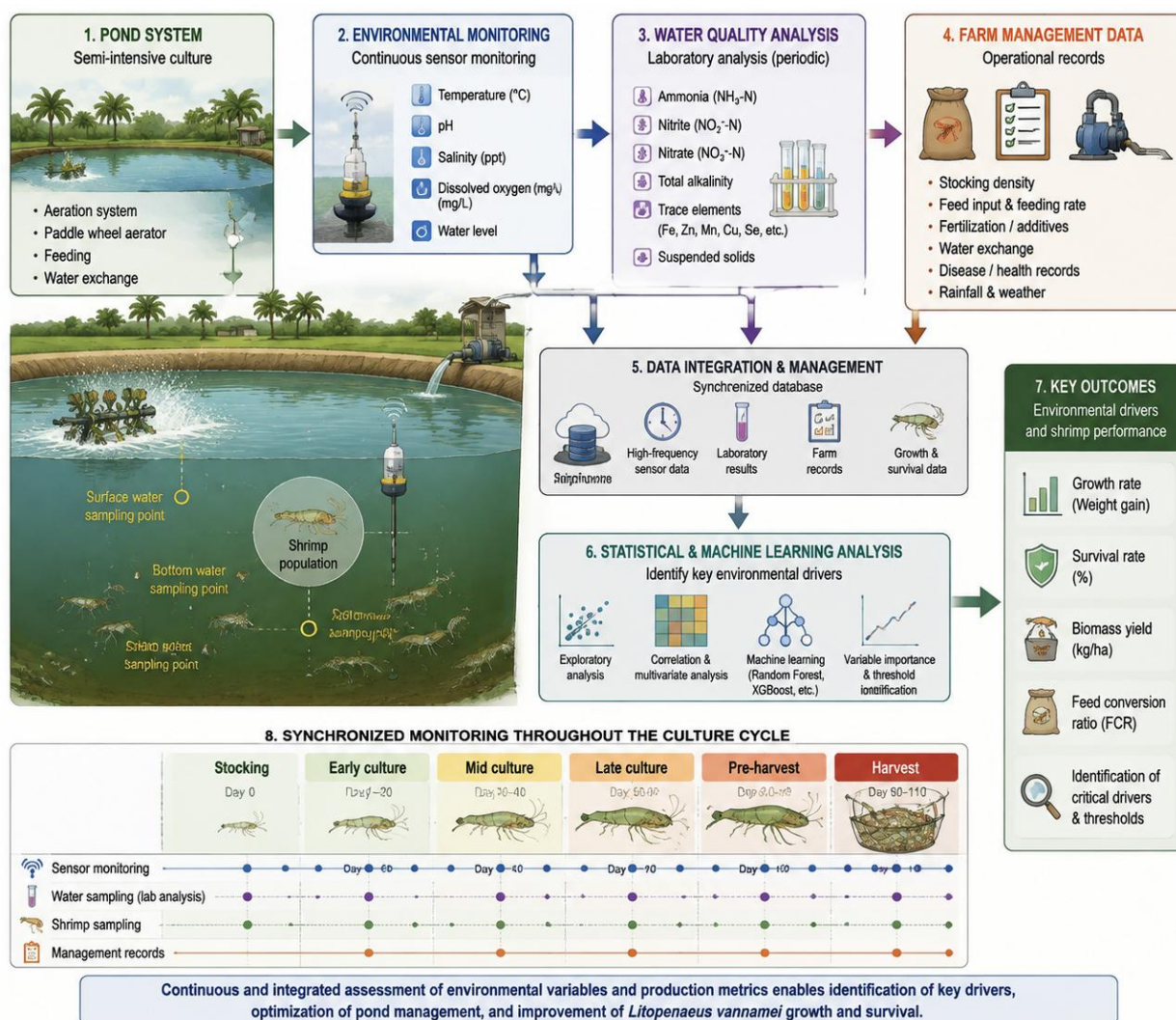


Figure 2 Integrated environmental monitoring framework for identifying environmental drivers of *Litopenaeus vannamei* growth and survival in pond aquaculture systems

6.3 Management implications derived from statistical results

The main management implication from these statistical results is that production gains depend less on any single target value than on maintaining stable, favorable water-quality conditions throughout the cycle. In commercial semi-intensive farms, dissolved oxygen showed a strong positive association with shrimp body weight and temperature showed negative correlations with survival and daily growth, while a separate regression-based sensitivity analysis found that dissolved oxygen variability had the largest effect on final production among the tested variables (Ruiz-Velazco et al., 2022). These findings support a management priority on aeration, oxygen stability, and rapid correction of thermal stress rather than relying only on feed or stocking adjustments (Srinivasan et al., 2025).

Statistical results also support broader operational decisions on stocking, water exchange, disease prevention, and long-term husbandry improvement. Water-quality suitability studies found that moderate stocking density and low-to-moderate water exchange improved shrimp productivity and water-use efficiency, while survey-based logistic regression in the Mekong region showed that disease risk was lowered by routine feed conversion calculations, training participation, and adaptive feeding responses to climatic events (Le et al., 2024). At the breeding and farm-management level, mixed-model evidence further suggests that improvements in aeration, water quality, stocking density, feed, and feeding regimes can mitigate biologically significant genotype-by-environment effects, indicating that statistical assessment should inform not only pond operations but also longer-term production strategy.

7 Integration of Statistical Models into Precision Shrimp Aquaculture Management

7.1 Development of data-driven aquaculture decision systems

Data-driven aquaculture decision systems increasingly combine continuous environmental sensing, predictive analytics, and user-facing dashboards to support faster and more consistent farm management. A real-time shrimp monitoring system in Bangladesh integrated IoT devices, cloud services, machine learning models, and web applications to track pH, temperature, total dissolved solids, electrical conductivity, and salinity, while also issuing alerts when parameters moved outside optimal ranges (Ahmed et al., 2024). A broader decision-support framework similarly proposed a multi-source data hub that merges environmental, trading, and internet-derived data into a common platform, with modules for environmental monitoring, equipment sharing, cost-profit calculation, and price prediction (Le et al., 2024).

These systems are valuable because they replace fragmented manual observation with structured, stage-specific decision support. Bayesian belief network work in rice-shrimp farming showed that environmental conditions, stocking density, and fertilizer use can be encoded into a decision model that identifies action sets reducing the probability of crop failure, and that systematic interrogation across crop stages helps farmers make timely choices. More recent anomaly-detection research in commercial shrimp ponds also found that routine measurements of salinity, alkalinity, hardness, and inorganic nitrogen can reliably distinguish acceptable from residual water status, supporting low-cost operational warning signals in data-limited settings (Villamar-Barros et al., 2026).

7.2 Application of artificial intelligence and big-data analytics

Artificial intelligence is now used in shrimp aquaculture not only for water-quality prediction but also for feeding, biomass estimation, reproduction management, and production classification. In recirculating systems for *Litopenaeus vannamei*, a data-driven biomass model built from water-quality and management variables showed that support vector machines achieved the best predictive performance, and the resulting model was used to determine appropriate feeding amounts in real time (Chen et al., 2024). In broodstock management for *Penaeus monodon*, a two-stage machine-learning framework predicted both molting and ovarian maturation, with random forest reaching 88.5% accuracy and 94.3% AUC, indicating that AI can also support precision control of reproductive timing (Yang et al., 2025).

Big-data analytics has also expanded into computer vision and multiyear industrial modeling. Deep-learning shrimp counting in industrial recirculating farms outperformed manual counting, and the best model achieved 5.97% error at densities below 200 shrimp per image, bringing automated stock estimation close to deployment thresholds. In industrial-scale outdoor white shrimp farming, five years of data from 12 ponds showed that ensemble machine learning predicted body weight with $R^2 = 0.829$, while explainability analysis indicated that days of culture, stocking density, and cumulative feed ranked above temperature, pH, and dissolved oxygen in predictive importance.

7.3 Future perspectives for sustainable shrimp production

Future precision shrimp aquaculture appears to depend on integrating AI with streaming data architectures, edge computing, and accessible decision-support systems. A recent systematic review found that LSTM, GRU, and CNN models perform strongly for predicting dissolved oxygen, pH, and temperature, while IoT sensors, UAVs, and AI-based imaging systems enable high-speed environmental and behavioral monitoring; however, the same review identified persistent challenges in standardization, scalability, and long-term validation. A broader review of AI for sustainable aquaculture likewise concluded that predictive modeling and decision-support systems are central to precision production, but adoption is still limited by data heterogeneity, sensor reliability, and the socio-economic digital divide between high-tech and small-scale systems.

Sustainable implementation will therefore require not only better models, but also more inclusive innovation systems, farmer training, and governance structures. Reviews focused on shrimp-sector technology emphasize that AI-enabled monitoring, automation, alternative feeds, and microbial approaches can improve productivity, animal health, and environmental performance, yet uptake remains constrained by capital cost, technical complexity, and uneven access to digital tools. Complementary work on digital sustainability in Indonesia further suggests that end-

to-end digital services can optimize feed use, reduce waste, improve profitability, and empower small-scale shrimp farmers when innovation is built around stakeholder partnerships rather than technology alone (Izharuddin, 2025).

8 Conclusions

Across the reviewed studies, shrimp performance was consistently linked to core environmental variables, especially dissolved oxygen, temperature, salinity, and nitrogenous wastes. In semi-intensive farms, dissolved oxygen was positively associated with body weight, while higher temperature was negatively associated with survival and average daily growth, and parallel pond studies likewise concluded that temperature, pH, salinity, ammonia, and dissolved oxygen must be kept within favorable ranges through routine management. These findings support the broader conclusion that shrimp growth and survival are regulated by the combined stability of multiple environmental parameters rather than by any single variable alone.

Experimental evidence also shows that environmental effects are often nonlinear and interactive. Response-surface analysis in biofloc nursery production found that survival remained above 84.5% at 24°C–28°C but declined as temperature increased from 28 to 32°C, while growth and survival were jointly optimized near 27.25°C and 25.5 g/L salinity. Salinity effects were further confirmed in hatchery-stage experiments, although the apparent optimum varied by developmental stage and system, with one study reporting the highest post-larval performance at 26 ppt and another reporting the best survival at 33 ppt, indicating that salinity targets should be interpreted in relation to age class and culture context.

Statistical analysis has contributed most clearly by converting routine environmental measurements into decision-relevant estimates of production risk and performance. Pond-scale studies used variance analysis, correlation analysis, and simple linear regression to identify which environmental variables differed significantly among ponds and which ones most strongly predicted final weight and survival, with dissolved oxygen emerging as one of the most influential drivers of production. Even relatively simple multiple linear regression frameworks have shown that temperature, salinity, pH, and dissolved oxygen can jointly explain shrimp-age-related variation in intensive ponds, supporting the practical value of statistical screening before more advanced modeling is applied.

More recent work extends these contributions from interpretation to automation, prediction, and farm-level intervention. Real-time IoT systems coupled with regression and classification models predicted next-day pond conditions with $R^2 = 0.94$ and classified shrimp production levels with 97.84% accuracy, while integrated IoT–machine learning systems in aquaculture more broadly achieved high predictive accuracy and supported over 6000 corrective interventions while maintaining survival above 90%. Statistical and machine-learning approaches therefore now function not only as analytical tools for understanding environmental effects, but also as operational tools for continuous monitoring, rapid response, and improved management efficiency.

Future research should move toward more integrated, high-frequency, and spatially explicit environmental assessment. Recent reviews indicate that deep learning models such as LSTM, GRU, and CNN perform well for predicting dissolved oxygen, pH, and temperature from streaming data, but they also emphasize unresolved needs for benchmarking, hybrid edge-cloud architectures, and long-term validation across shrimp systems. In parallel, ecosystem-modeling work recommends stronger adoption of autonomous monitoring and three-dimensional modeling, because current simulations still struggle to reproduce sudden dissolved oxygen drops and other fast fluctuations that increase production risk.

A second priority is to connect pond-level environmental statistics with broader sustainability and management outcomes. Meta-analytic evidence suggests that survival rate, pH, and dissolved oxygen all influence the comprehensive benefits of different farming models, and that future work should incorporate dynamic models to simulate long-term benefit trends under changing production strategies. Life-cycle assessment reviews further show that future environmental analysis should extend beyond pond water quality alone to include feed formulation, farm energy use, feed conversion, nutrient discharges, and renewable energy integration, so that shrimp production can be optimized for both biological performance and environmental sustainability.

References

- Ahmed F., Bijoy M.H.I., Hemal H.R., and Noori S.R.H., 2024, Smart aquaculture analytics: Enhancing shrimp farming in Bangladesh through real-time IoT monitoring and predictive machine learning analysis, *Heliyon*, 10(17): e37330.
<https://doi.org/10.1016/j.heliyon.2024.e37330>
- Akbarurasyid M., Prama E.A., Sembiring K., Anjarsari M., Sofian A., and Astiyani W.P., 2023, Monitoring of aquatic environmental factors on the growth of whiteleg shrimp (*Litopenaeus vannamei* Boone, 1931), *Jurnal Perikanan Universitas Gadjah Mada*, 25(2): 181-188.
<https://doi.org/10.22146/jfs.83813>
- Araneda M., Gasca-Leyva E., Vela M.A., and Domínguez-May R., 2020, Effects of temperature and stocking density on intensive culture of Pacific white shrimp in freshwater, *Journal of Thermal Biology*, 94: 102756.
<https://doi.org/10.1016/j.jtherbio.2020.102756>
- Arfati D., Buwono N., Musa M., Prihanto A.A., Maftuch M., Mahmudi M., Dailami M., Amin A.A., Rangkuti R.F.A., and Lusiana E., 2025, A comparative analysis of machine learning regression models of whiteleg shrimp growth reared in eco-green aquaculture system, *Ecological Engineering & Environmental Technology*, 26(6): 146-154.
<https://doi.org/10.12912/27197050/204080>
- Chen F., Qiu T., Xu J., Zhang J., Du Y., Duan Y., Zeng Y., Zhou L., Sun J., and Sun M., 2024, Rapid real-time prediction techniques for ammonia and nitrite in high-density shrimp farming in recirculating aquaculture systems, *Fishes*, 9(10): 386.
<https://doi.org/10.3390/fishes9100386>
- Flores-Iwasaki M., Guadalupe G.A., Pachas-Caycho M., Chapa-Gonza S., Mori-Zabarburú R.C., and Guerrero-Abad J., 2025, Internet of Things (IoT) sensors for water quality monitoring in aquaculture systems: A systematic review and bibliometric analysis, *AgriEngineering*, 7(3): 78.
<https://doi.org/10.3390/agriengineering7030078>
- Han L., Yan P., and Wang M., 2025, Comparative analysis on survival and tissue damage of different environmental stress factors in Pacific white shrimp *Litopenaeus vannamei*, *Comparative Immunology Reports*, 8: 200219.
<https://doi.org/10.1016/j.cirep.2025.200219>
- Izharuddin M., 2025, Institutionalized digital sustainability in aquaculture: End-to-end digitally enabled innovation, *International Journal of Innovation Science*, 17(4): 999-1022.
<https://doi.org/10.1108/IJIS-06-2024-0160>
- Le N.T.T., Armstrong C.W., Brækkan E., and Eide A., 2024, Climatic events and disease occurrence in intensive *Litopenaeus vannamei* shrimp farming in the Mekong area of Vietnam, *Aquaculture*, 587: 740867.
<https://doi.org/10.1016/j.aquaculture.2024.740867>
- Li X., Wang L., and Dai X., 2024, Combined effects of ammonia nitrogen, nitrite, salinity, and temperature negatively impact the growth, survival, physiological, and biochemical parameters, and hepatopancreatic structure of *Litopenaeus vannamei*, *Aquaculture*, 596: 741845.
<https://doi.org/10.1016/j.aquaculture.2024.741845>
- Millard R.S., Ellis R., Bateman K., Bickley L., Tyler C., Van Aerle R., and Santos E., 2020, How do abiotic environmental conditions influence shrimp susceptibility to disease? A critical analysis focussed on White Spot Disease, *Journal of Invertebrate Pathology*, 186: 107369.
<https://doi.org/10.1016/j.jip.2020.107369>
- Mustafa A., Paena M., Athirah A., Ratnawati E., Asaf R., Suwoyo H.S., Sahabuddin S., Hendrajat E.A., Kamaruddin K., Septiningsih E., Sahrijanna A., Marzuki I., and Nisaa K., 2022, Temporal and spatial analysis of coastal water quality to support application of whiteleg shrimp *Litopenaeus vannamei* intensive pond technology, *Sustainability*, 14(5): 2659.
<https://doi.org/10.3390/su14052659>
- Nazarudin M.F., Zulkiply M.A.F., Samsuri M., Anwar N.A.S.K., Jamal N.S.A., Alipiah N., Ahmad M.I., Nor N.M., Yasin I.S.M., Ikhsan N., Azmai M.N.A., and Rosli M.H., 2025, Optimizing shrimp culture through environmental monitoring: Effects of water quality and metal ion profile on whiteleg shrimp (*Litopenaeus vannamei*) performance in a semi-intensive culture pond, *Water*, 17(19): 2818.
<https://doi.org/10.3390/w17192818>
- Ruiz-Velazco J.M., Estrada-Pérez N., Estrada-Pérez M., Zavala-Leal I., Valdez-González F., Cuevas-Rodríguez B., and González-Huerta C.A., 2022, Predicting semi-intensive production of *Penaeus vannamei* using simple linear regression models: A sensitivity analysis using environmental and management variables, *Revista Bio Ciencias*, 9: e1347.
<https://doi.org/10.15741/revbio.09.e1347>
- Srinivasan V., Kumar D.S., Thirunavukkarasu N., Nesakumari C.S.A., and Yuvaraj D., 2025, Water quality dynamics and their impact on growth performance of *Litopenaeus vannamei* in semi-intensive farms along southeast coast of India, *International Journal of Environmental Sciences*, 2025: 2167-2179.
<https://doi.org/10.64252/arrvqb33>
- Thai-Nghe N., Thanh-Hai N., and Ngõn N.C., 2020, Deep learning approach for forecasting water quality in IoT systems, *International Journal of Advanced Computer Science and Applications*, 11(8): 686-693.
<https://doi.org/10.14569/IJACSA.2020.0110883>
- Tuyen T., Al-Ansari N., Nguyen D.D., Le H.M., Phan T., Prakash I., Costache R., and Pham B.T., 2023, Prediction of white spot disease susceptibility in shrimps using decision trees based machine learning models, *Applied Water Science*, 14(1): 2.
<https://doi.org/10.1007/s13201-023-02049-3>

- Udayakumar R., Alhassan A., Abbas Z., Jayanthi K.B., Husain S.O., Shavkidinova D., Kadirov I., and Shodiyev A., 2025, Forecasting disease outbreaks in shrimp aquaculture using LSTM deep learning models, Natural and Engineering Sciences, 10(3): 371.
<https://doi.org/10.28978/nesciences.1811130>
- Villamar-Barros H., Coronel-Reyes J., and Haro-Sarango A., 2026, Early anomaly detection in shrimp pond water quality using supervised and unsupervised machine learning models, Digital, 6(2): 27.
<https://doi.org/10.3390/digital6020027>
- Yang H.Y., Chou H.H., Hung L.J., Huang J.Y., Tien N.Y., Wang H., and Hsieh S.Y., 2025, Machine learning approach for predicting ovarian maturation in *Penaeus monodon*, Smart Agricultural Technology, 2025: 101597.
<https://doi.org/10.1016/j.atech.2025.101597>
- Zarzar C.A., Fernandes T.J., and Oliveira I.R.C.D., 2023, Modeling the growth of Pacific white shrimp (*Litopenaeus vannamei*) using the new Bayesian hierarchical approach based on correcting bias caused by incomplete or limited data, Ecological Informatics, 77: 102271.
<https://doi.org/10.1016/j.ecoinf.2023.102271>
- Zhao M.M., Yao D., Li S., Zhang Y., and Aweya J., 2020, Effects of ammonia on shrimp physiology and immunity: A review, Reviews in Aquaculture, 12(4): 2194-2211.
<https://doi.org/10.1111/raq.12429>



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Research Insight

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Microbial Monitoring-Based Health Management Models for Marine Aquaculture

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Abstract Marine aquaculture is moving toward greater production intensity while facing persistent challenges from infectious disease, environmental instability, and antimicrobial resistance. In this setting, microbial communities should no longer be treated only as a background component of the culture environment. They participate in nutrient cycling, organic matter transformation, host nutrition, mucosal defense, pathogen exclusion, and disease development. This review examines how microbial monitoring can be translated from a descriptive research tool into a practical component of marine aquaculture health management. Conventional culture, PCR-based assays, 16S rRNA gene sequencing, metagenomics, multi-omics approaches, flow cytometry, biosensors, and field-deployable molecular methods provide complementary information at different levels of taxonomic, functional, quantitative, and temporal resolution. Particular attention is given to potential pathogens, health-associated microorganisms, community stability, dysbiosis, and functional genes as candidate indicators. Current evidence indicates, however, that no single microbial taxon or diversity metric can serve as a universal marker of health. Monitoring is most informative when microbial signals are interpreted against farm-specific baselines and integrated with water quality, production stage, and host-health observations. On this basis, the review proposes a tiered framework linking routine surveillance, early warning, risk classification, proportionate intervention, and post-intervention feedback. The framework intentionally avoids fixed universal thresholds because microbial communities vary substantially among species, farms, seasons, and production systems. Future progress will depend on standardized sampling, absolute microbial quantification, longitudinal and multi-farm validation, functional confirmation of biomarkers, and integration of rapid microbial monitoring with environmental sensors and data-driven decision support. Microbial monitoring can therefore support a gradual shift from reactive treatment of disease toward preventive, adaptive, and precision health management in sustainable marine aquaculture.

Keywords Marine aquaculture; Microbial monitoring; Microbiome; Microbial dysbiosis; Health management; Disease early warning; Microbial indicators; Sustainable aquaculture

1 Introduction

Aquaculture has become increasingly important to global aquatic food production, and its continued expansion is central to meeting demand for aquatic foods without relying solely on capture fisheries. The Food and Agriculture Organization reported that aquaculture surpassed capture fisheries in aquatic animal production in 2022, highlighting both its growing contribution and the need to improve biological and environmental sustainability. Intensification, however, concentrates animals, feed inputs, organic matter, and microorganisms within comparatively restricted environments. Disease remains one of the major biological constraints on aquaculture, while environmental change, pathogen transmission, and antimicrobial resistance complicate conventional health management (Naylor et al., 2021).

Traditional aquatic animal health management has largely focused on recognizable pathogens: detect the causative agent, confirm disease, and then intervene. Such a strategy remains essential during outbreaks, but it is inherently reactive. It may also overlook the ecological transition that occurs before obvious clinical signs appear. International aquatic animal health guidance increasingly combines disease control with biosecurity, surveillance, prevention, and responsible antimicrobial use rather than relying on treatment alone. At the farm level, the unresolved question is how to recognize a deteriorating biological state early enough for low-impact intervention to be useful.

Microbial ecology offers a way to address this gap. An aquaculture animal lives within a connected microbial landscape comprising the surrounding water, sediment, tank or cage surfaces, feed, biofilms, and microorganisms associated with the gut, gills, skin, and mucus. These assemblages are not static. They respond to animal development, temperature, salinity, nutrient loading, husbandry, disease, and treatment. In a 13-month survey of Sanggou Bay mariculture, for example, seasonality strongly structured bacterioplankton communities, while potentially pathogenic *Vibrio* became more prominent during late-summer and autumn high-risk periods (Lu et al., 2025). Longitudinal studies in fish, shrimp, and hatchery shellfish similarly show that temporal context is indispensable when microbiomes are interpreted as health indicators (Cram et al., 2024; Bui et al., 2026).

The concept of microbial dysbiosis extends this perspective beyond pathogen abundance. Dysbiosis refers to an unfavorable departure from a host- or system-associated microbial state and may include community restructuring, loss of potentially protective organisms, proliferation of opportunists, altered interactions, or changed microbial functions. Reviews of aquaculture microbiomes have proposed such changes as potential disease biomarkers, while also warning that a universal “healthy microbiome” has not yet been defined (Infante Villamil et al., 2021; Mougin and Joyce, 2023). The distinction matters: a microbial change can precede disease, result from disease, or simply reflect a normal environmental transition.

Technological advances make this ecological information increasingly accessible. Targeted qPCR and digital PCR provide sensitive quantification; 16S rRNA sequencing reveals broad community structure; shotgun metagenomics can recover genes and genomes; metabolomics and transcriptomics add functional information; and rapid approaches such as flow cytometry and isothermal amplification shorten the interval between sampling and interpretation. Field-oriented LAMP assays for marine *Vibrio* illustrate how molecular detection is beginning to move from specialized laboratories toward farm-side surveillance (Rahman et al., 2022; Pu et al., 2026).

The purpose of this review is therefore not to present microbiome sequencing as a replacement for veterinary diagnosis, water-quality monitoring, or conventional biosecurity. Rather, it examines how microbial information can be integrated with those practices to create a more anticipatory health-management system. The discussion moves from microbial ecology and monitoring technologies to candidate health indicators, environmental drivers, early-warning strategies, practical management models, and applications across major marine aquaculture systems. The central argument is that the greatest value of microbial monitoring lies not in identifying a universal “good” or “bad” bacterium, but in detecting meaningful deviations from a well-characterized biological baseline early enough to support proportionate management.

2 Microbial Communities and Health in Marine Aquaculture Systems

2.1 Composition and ecological functions of microbial communities

Marine aquaculture systems contain overlapping but non-identical microbial habitats. Water-column communities respond rapidly to temperature, nutrient availability, phytoplankton, dissolved organic matter, and hydrodynamics, whereas sediment and biofilm communities experience stronger gradients in oxygen and organic loading. Host-associated communities add another level of selection because the gut, gills, skin, and mucus provide distinct physicochemical conditions. Even within a single shrimp, gastrointestinal compartments can contain different community structures, emphasizing that “the microbiome” is not one uniform biological compartment (Garibay-Valdez et al., 2021).

These microorganisms collectively contribute to organic matter degradation and carbon, nitrogen, and sulfur transformations while competing, cooperating, and exchanging metabolites with one another. In biofloc shrimp systems, rearing-water communities show clear succession during the production cycle, with different bacterial groups becoming prominent at different stages (Kim et al., 2022). Metagenomic comparison of grouper cage waters and nearby non-aquaculture waters has likewise linked aquaculture-related nutrient enrichment with shifts in both microbial composition and predicted biogeochemical functions (Liu et al., 2024).

2.2 Host-Microbiome interactions in cultured marine animals

Host-associated microbiota occupy interfaces where nutrition, immunity, and environmental exposure meet. Gut microorganisms can participate in nutrient transformation and production of metabolites, while mucosal communities on the skin and gills interact directly with host defenses and incoming environmental microorganisms. Research across fish increasingly supports the view that host identity, development, environment, and diet jointly structure these communities rather than one factor acting independently (Yajima et al., 2023; Zhao et al., 2023).

A protective microbiome should nevertheless be understood functionally rather than as a fixed list of beneficial taxa. Some resident organisms may occupy niches that would otherwise be available to pathogens, produce antagonistic compounds, or influence mucosal immune responses. Conversely, a normally harmless member may become problematic when environmental conditions or host defenses change. This context dependence is especially important in aquaculture, where the same bacterial genus may contain commensal, probiotic, and pathogenic strains. Consequently, genus-level sequence data should rarely be interpreted as direct evidence of disease or protection (Mougin and Joyce, 2023).

2.3 Microbial homeostasis and dysbiosis

Microbial homeostasis is better described as a resilient range than a constant community composition. A healthy animal or production system can undergo substantial temporal turnover while retaining important ecological functions. Atlantic salmon gill communities, for example, restructure through the marine production cycle, and not every change in richness or diversity corresponds to poorer gill health (Clinton et al., 2024). This finding argues against using a single diversity index as a universal health threshold.

Dysbiosis becomes more informative when several signals converge: abrupt community turnover, enrichment of opportunists, loss of persistent host-associated taxa, altered network structure, functional changes, and measurable deterioration of host or environmental condition. In shrimp white feces syndrome, experimental work provided evidence that altered intestinal microbiota can contribute to disease processes rather than merely reflect them (Huang et al., 2020). Yet causality should not be assumed in every system. Oyster hatchery research has shown that some microorganisms enriched during production crashes appear to proliferate after host deterioration rather than initiate it (Cram et al., 2024).

3 Microbial Monitoring Technologies for Marine Aquaculture

3.1 Conventional microbial monitoring methods

Culture-dependent microbiology remains useful because isolates can be phenotyped, tested for pathogenicity or antimicrobial susceptibility, preserved, and examined experimentally. Selective media and colony enumeration are relatively inexpensive and provide information on culturable populations that molecular surveys alone cannot deliver. Their principal weakness is incomplete coverage: many environmental microorganisms are difficult to culture under routine laboratory conditions, while culture and biochemical identification may take longer than desirable during rapidly developing disease events (Rahman et al., 2022).

The most practical strategy is therefore complementary rather than competitive. Culture is particularly valuable when an isolate is required for challenge testing, antimicrobial susceptibility, genomic characterization, or probiotic development; sequence-based and molecular methods are better suited to broad surveillance and rapid detection. Maintaining this distinction prevents the common error of treating a DNA sequence as equivalent to a viable pathogenic organism.

3.2 Molecular detection of target microorganisms

PCR and qPCR transformed pathogen surveillance by allowing specific microbial targets to be detected without lengthy cultivation. qPCR additionally estimates target abundance, making it more useful for longitudinal monitoring than simple presence/absence testing. Digital PCR partitions reactions and can provide absolute nucleic-acid quantification without a conventional calibration curve. In seawater experiments, a propidium-monoazide-ddPCR approach was able to distinguish viable-target DNA from dead-cell DNA for toxigenic *Vibrio cholerae*,

illustrating how viability and absolute quantification can be incorporated into environmental surveillance (Yang et al., 2023).

The limitation of targeted assays is equally clear: they detect what investigators decide to search for. A well-designed qPCR panel can be highly useful when key pathogens and virulence markers are known, but it cannot describe an unexpected community-wide shift. For health management, targeted PCR is therefore best positioned as a rapid confirmation layer within a broader monitoring program.

3.3 16S rRNA gene amplicon sequencing

16S rRNA gene sequencing remains one of the most accessible approaches for characterizing bacterial and archaeal communities. It can compare alpha diversity, community dissimilarity, taxonomic composition, succession, and candidate indicator taxa across time, farms, tissues, or health states. Longitudinal shrimp, salmon, oyster, and barramundi studies demonstrate how these profiles can reveal microbial changes that are invisible to routine culture or single-target assays (Kim et al., 2022; Cram et al., 2024).

Its interpretation requires restraint. Amplicon sequencing normally reports relative rather than absolute abundance; taxonomic resolution can be insufficient to distinguish pathogenic and non-pathogenic strains; primer choice and DNA extraction introduce bias; and detection of bacterial DNA does not prove viability or virulence. Bui et al. (2026) found that 16S sequencing and flow-cytometric community fingerprints captured complementary aspects of microbial dynamics in commercial barramundi larviculture, reinforcing the value of combining rather than substituting methods.

3.4 Metagenomic and metatranscriptomic approaches

Shotgun metagenomics extends monitoring from marker genes to the broader genetic potential of a community. It can provide improved taxonomic resolution and detect genes related to metabolism, virulence, nutrient cycling, and antimicrobial resistance. In marine cage aquaculture, metagenomic analysis has revealed differences in both taxonomic composition and carbon-, nitrogen-, and sulfur-related functional profiles between aquaculture and nearby non-aquaculture waters (Liu et al., 2024). Such information may eventually help distinguish a harmless taxonomic shift from a functionally consequential one.

Metatranscriptomics adds another dimension by measuring expressed RNA and thus providing a closer view of microbial activity. Its practical barriers are cost, RNA instability, bioinformatic complexity, and the difficulty of separating biologically meaningful signals from short-term environmental responses. These approaches are therefore most valuable today for biomarker discovery and mechanistic research rather than routine monitoring of every production unit.

3.5 Multi-Omics approaches to microbial health monitoring

No single omics layer fully describes host–microbe–environment interactions. Metagenomics indicates functional potential, metatranscriptomics identifies active expression, metabolomics characterizes chemical outputs, and proteomics can reveal expressed proteins. Integrating these layers may therefore separate taxonomic change from functional change and identify mechanisms that would remain hidden in a 16S dataset alone.

This potential is illustrated by integrated metagenomic and metabolomic analysis of *Litopenaeus vannamei* exposed to microcystin-LR, where microbial functional shifts were examined together with altered intestinal metabolites (Duan et al., 2022). The study also illustrates a broader caution: multi-omics produces many associations, but candidate biomarkers still require experimental validation before becoming operational health indicators.

3.6 Rapid and on-site microbial detection technologies

Farm health decisions often require information faster than conventional sequencing can provide. Isothermal amplification, portable nucleic-acid platforms, biosensors, microfluidics, and high-throughput flow cytometry are attractive because they can reduce analytical turnaround. A LAMP assay developed for *Vibrio harveyi* demonstrated rapid target detection under isothermal conditions, and a more recent direct LAMP workflow for *V.*

parahaemolyticus was specifically tested with shrimp aquaculture water and designed around field deployment (Rahman et al., 2022; Pu et al., 2026).

Flow cytometry offers a different advantage: it rapidly measures phenotypic distributions of microbial cells without first knowing their taxonomy. Machine-learning analysis has shown that flow-cytometric fingerprints can contain information associated with bacterial community composition, although taxonomic abundance prediction remains imperfect (Heyse et al., 2021). In barramundi hatcheries, FCM and 16S sequencing showed complementary trends, suggesting a feasible future division of labor in which rapid fingerprints flag unusual community states and sequencing is reserved for diagnostic clarification (Figure 1) (Bui et al., 2026).

	Taxonomic breadth	Functional resolution	Quantification capability	Analytical speed	Field deployability	Operational complexity / cost
Culture-dependent methods	Low	Low	Medium	Medium	Low	Medium
qPCR / dPCR	Low	Low	High	High	Medium	Medium
16S rRNA sequencing	High	Medium	Medium	Medium	Low	High
Shotgun metagenomics	High	High	Medium	Low	Low	High
Multi-omics	High	High	Low	Low	Low	High
Flow cytometry (FCM)	Low	Low	Medium	High	High	Medium
LAMP / biosensors	Low	Low	Medium	High	High	Low

Low
 Medium
 High

Methods are complementary; no single platform is optimal for all monitoring purposes.

Figure 1 Comparison of major microbial monitoring technologies for marine aquaculture health management

4 Microbial Indicators for Health Assessment in Marine Aquaculture

4.1 Potential pathogenic microorganisms as risk indicators

Potential pathogens remain necessary indicators because an increasing pathogen burden can mark rising infection pressure. In marine aquaculture, *Vibrio*, *Photobacterium*, and *Tenacibaculum* are particularly relevant in many fish, shrimp, and shellfish contexts, while *Aeromonas* and other opportunistic genera are important in particular host and environmental settings. Long-term Sanggou Bay monitoring found seasonal enrichment of potentially pathogenic *Vibrio*, and experimental shrimp studies show that *Vibrio harveyi* exposure can restructure the gut community (Deris et al., 2022; Lu et al., 2025).

Nevertheless, genus-level detection alone is a weak diagnostic criterion. Different *Vibrio* lineages have sharply different ecological roles and virulence potential. Oyster hatchery monitoring provides a useful warning: *Vibrio* groups observed during some larval crashes appeared more likely to respond to deterioration than to initiate it (Cram et al., 2024). Pathogen surveillance should therefore combine abundance, species or strain identity where possible, virulence markers, host signs, and environmental context.

4.2 Beneficial and health-associated microorganisms

Positive indicators can be as informative as pathogens if they represent persistent organisms associated with a resilient host or culture environment. Candidate beneficial bacteria may suppress pathogens through competition, antimicrobial production, resource exclusion, or modification of the local environment. Roseobacter-group *Phaeobacter*, for example, has been studied as a probiotic candidate because some strains inhibit important aquaculture pathogens (Sonnenschein et al., 2021).

Yet “beneficial” should not become another taxonomic shortcut. Performance depends on strain, host, diet, dose, environment, and microbial community context. Dietary supplementation with *Pseudoalteromonas piscicida* and fructooligosaccharide has produced beneficial outcomes in experimental whiteleg shrimp, but such results do not justify classifying every *Pseudoalteromonas* as beneficial (Nababan et al., 2022). Positive indicators should therefore be validated at strain or function level and against defined production outcomes.

4.3 Microbial diversity and community stability

Diversity metrics are attractive because they compress complex communities into simple numbers, but their biological meaning is context dependent. A sudden diversity loss can accompany dysbiosis, yet high diversity is not automatically equivalent to health. Communities may naturally change during host development, system maturation, feed transitions, or seasonal shifts. Biofloc shrimp culture, for instance, shows substantial stage-dependent succession even during successful production (Kim et al., 2022).

Temporal stability, resilience after disturbance, and deviation from a farm-specific reference state may therefore be more useful than an isolated Shannon or Chao1 value. Clinton et al. (2024) found specific Atlantic salmon gill taxa associated with different health states even though general richness and diversity were not consistently related to pathology. This supports a multidimensional interpretation in which diversity is contextual evidence rather than a stand-alone diagnosis.

4.4 Microbial dysbiosis as an early-warning indicator

Dysbiosis is especially promising for early warning because disease may emerge from a broader ecological destabilization rather than a single pathogen crossing a universal threshold. Candidate warning signals include unusual community turnover, expansion of opportunists, disappearance of persistent taxa, loss of network complexity, and changed community functions. Reviews of aquaculture microbiomes identify these patterns as plausible biomarkers but emphasize their strong host and environmental dependence (Mougin and Joyce, 2023; Xavier et al., 2024).

The timing of dysbiosis is decisive. A useful warning indicator must change before irreversible host deterioration, not merely describe a sick animal. In oyster larvae, community structure at an early developmental stage showed associations with later batch performance, while many taxa appearing during crashes were probably secondary responders (Cram et al., 2024). This distinction argues strongly for dense longitudinal sampling in biomarker-discovery studies.

4.5 Functional microbial indicators

Functional markers may sometimes generalize better than specific taxa because similar ecological functions can be performed by different organisms. Potential examples include virulence genes, antimicrobial-resistance determinants, nitrogen-cycle genes, oxidative-stress responses, and metabolite-production pathways. Metagenomic surveys can therefore ask not only “who is present?” but also “what biological capabilities are becoming more or less abundant?” (Liu et al., 2024).

A practical monitoring system might eventually combine a small taxonomic panel with a functionally informative gene panel. This would be particularly valuable where strain-level pathogenicity differs within a genus. Functional indicators still require careful interpretation because gene presence does not prove expression, while metatranscriptomic or metabolomic activity can be transient. Their main advantage is thus mechanistic specificity, not automatic diagnostic certainty.

5 Major Factors Shaping Microbial Health in Marine Aquaculture

5.1 Water quality and environmental conditions

Microbial communities respond quickly to the physical and chemical environment. Temperature influences growth rates and seasonal succession; salinity filters taxa according to osmotic tolerance; dissolved oxygen affects aerobic and anaerobic processes; and pH, ammonia, nitrite, and organic matter alter both microbial metabolism and host stress. In Sanggou Bay, temperature, dissolved oxygen, and transparency were significantly associated with bacterioplankton dynamics and seasonal pathogen patterns (Lu et al., 2025).

These relationships are rarely linear or universal. Experimental shrimp work showed that salinity interacted with *V. harveyi* exposure to reshape gut-community structure and network properties (Deris et al., 2022). Monitoring schemes should consequently interpret microbial signals together with environmental trajectories rather than treating water chemistry and microbiology as separate data streams.

5.2 Stocking density and culture intensity

Higher culture intensity increases feed demand, waste production, host-to-host contact, and microbial exchange. These processes can stimulate heterotrophic growth and create niches for opportunistic organisms, particularly when oxygen supply or waste removal becomes limiting. The effect is not simply “high density causes disease”; management technology determines how biological loading is handled.

For this reason, microbial monitoring may be most useful when interpreted relative to biomass and production stage. The same bacterial density can have different meanings early and late in a production cycle. Longitudinal biofloc observations demonstrate that microbial succession accompanies increasing culture age and organic loading, suggesting that stage-specific reference ranges are preferable to one farm-wide threshold (Kim et al., 2022).

5.3 Feed and feeding management

Feed influences microbial health through two pathways. Consumed feed changes the intestinal chemical environment and substrate availability, while uneaten feed and fecal material enter the surrounding system and stimulate environmental microorganisms. The resulting changes can alter oxygen demand, nutrient transformations, biofilm growth, and microbial exchange between water and host.

Feed management should therefore be included in microbial interpretation even when it is not the primary research variable. Studies comparing aquaculture management systems show that environmental and intestinal microbiomes respond to production practices, including probiotic and biofloc approaches (Waiho et al., 2023). Future farm baselines should record major diet transitions and feeding-rate changes so that ordinary nutritional responses are not misclassified as disease warnings.

5.4 Water exchange, aeration, and system management

Water exchange and aeration alter microbial dispersal, oxygenation, particle suspension, and resource availability. Recirculating systems add biological filtration, creating engineered microbial niches that perform essential nitrification and other transformations. These microorganisms can also disperse between system water and animal surfaces, making the boundary between “environmental” and “host-associated” microbiota particularly porous.

Atlantic salmon raised in RAS showed temporal changes in skin, gill, and water microbiomes, including a period interpreted as possible dysbiosis that later recovered (Lorgen-Ritchie et al., 2022). In biofloc shrimp systems, microbial communities also changed markedly as the system matured (Kim et al., 2022). These observations favor adaptive baselines tailored to system design rather than comparisons with a supposedly universal marine microbiome.

5.5 Antibiotics, disinfectants, and other chemical interventions

Chemical disease control can alter non-target microorganisms as well as pathogens. This matters because treatment may temporarily suppress one pathogen while changing ecological niches, selecting resistant populations, or disrupting host-associated communities. In gilthead seabream, bacterial infection and subsequent oxytetracycline

treatment were accompanied by restructuring of skin, gill, and gut microbiomes, with tissue-specific changes in diversity and taxonomic composition (Rosado et al., 2023).

The appropriate conclusion is not that antimicrobial treatment should never be used, but that it should be justified diagnostically and accompanied by good biosecurity and follow-up monitoring. This aligns with international guidance emphasizing responsible antimicrobial use and resistance surveillance in aquatic animals. Microbiome recovery after treatment may itself become a useful future management endpoint.

5.6 Biological and microbial interventions

Probiotics, prebiotics, synbiotics, biofloc, and microbial consortia aim to steer microbial ecology rather than simply eliminate microorganisms. Their mechanisms can include competition with pathogens, production of inhibitory metabolites, stimulation of host immunity, and improved transformation of wastes. Research on *Phaeobacter* and other candidate probiotics provides a mechanistic basis for such approaches, while shrimp feeding experiments demonstrate that microbial and prebiotic combinations can influence disease resistance under controlled conditions (Sonnenschein et al., 2021; Nababan et al., 2022).

More ambitious strategies—microbiome transplantation, synthetic communities, and microbiome engineering—remain largely experimental in aquaculture. Their promise should not be confused with readiness for routine farm use. Ecological persistence, biosafety, host specificity, horizontal gene transfer, regulatory requirements, and unintended community effects all need evaluation before deliberate microbiome manipulation becomes a standard management practice.

6 Microbial Monitoring for Disease Risk Assessment and Early Warning

6.1 From pathogen detection to ecosystem-level health monitoring

A pathogen-centered test asks whether a particular agent is present. Ecosystem-level surveillance asks a broader question: is the biological system moving away from its normal operating state? The second approach incorporates environmental microbiota, host-associated microbiota, water quality, husbandry, and clinical observations. It does not weaken pathogen diagnostics; instead, it determines when targeted diagnostics should be intensified.

This shift is supported by evidence that aquaculture disease is often accompanied by community-wide restructuring. In shrimp, fish, and oysters, disease-associated microbial patterns extend beyond the nominal pathogen, while environmental conditions can strongly modify these patterns (Huang et al., 2020; Clinton et al., 2024). A useful surveillance hierarchy is therefore broad screening first, targeted confirmation second, and intervention only after biological context has been considered.

6.2 Microbial signatures associated with pre-disease states

The most valuable biomarker is not necessarily the organism most abundant in a diseased sample. From a management perspective, earlier and moderately predictive signals can be more useful than perfect post-disease classification. Oyster hatchery observations are instructive because microbial differences were detectable before later production failure, whereas several organisms that dominated during crashes appeared to be consequences of deteriorating host condition (Cram et al., 2024).

This temporal requirement changes experimental design. Cross-sectional comparisons of “healthy” and “diseased” animals are valuable for generating hypotheses, but they cannot reliably determine whether microbial change precedes pathology. Longitudinal studies that repeatedly sample the same production units, record host outcomes, and retain environmental metadata are more appropriate for discovery of genuine early-warning signals. Recent commercial barramundi monitoring further demonstrates that even nominally similar tanks can develop distinct microbial trajectories, so replication at the tank level is essential (Bui et al., 2026).

6.3 Integration of microbial and environmental indicators

Microbial data become operationally meaningful when linked to conditions that farmers can observe or modify. A rising opportunistic-pathogen signal has different implications under stable temperature and oxygen than during

rapid warming, hypoxia, or deteriorating nitrogen conditions. Integrating these measurements can therefore distinguish random microbial fluctuation from an ecological transition with plausible biological consequences.

Sanggou Bay provides a field-scale example: seasonal bacterial restructuring and potentially pathogenic *Vibrio* patterns were analyzed alongside physicochemical variables rather than interpreted in isolation (Lu et al., 2025). The practical lesson is simple. A health dashboard should not contain “microbiome” as a separate compartment; microbial, environmental, husbandry, and host data should be treated as interacting dimensions of the same production system.

6.4 Microbial health risk classification

A three-level classification offers a practical way to translate continuous microbial variation into management decisions. The categories below are conceptual rather than validated universal thresholds. Numerical cutoffs should only be established after longitudinal calibration for a specific species, farm, production stage, sample type, and analytical method (Table 1).

Level I: Healthy

At this level, microbial measurements remain within an established farm- and stage-specific baseline. Potential pathogens are absent, low, or stable relative to historical observations; community turnover follows expected seasonal or developmental trajectories; environmental parameters remain acceptable; and animals show normal feeding, behavior, and survival. Routine monitoring continues without unnecessary intervention.

Level II: Alert

An alert should be triggered by convergence rather than one isolated result. Examples include repeated increases in an opportunistic pathogen, unexpected community displacement, reduced stability, disappearance of persistent health-associated taxa, or environmental stress occurring at the same time as microbial change. Sampling frequency should increase, the signal should be confirmed by an independent or targeted method, and modifiable husbandry factors should be reviewed before disease becomes clinically evident.

Level III: High Risk

High risk is characterized by multiple lines of evidence suggesting loss of system resilience: substantial pathogen enrichment or virulence-marker detection, persistent dysbiosis, unfavorable environmental change, and early host-health abnormalities. At this point, farm biosecurity and diagnostic procedures should be escalated, affected production units assessed separately, and any therapeutic intervention based on appropriate veterinary and laboratory evidence rather than microbiome data alone.

Table 1 Conceptual microbial indicators and corresponding management responses. These signals are intended for farm-specific calibration; they are not universal diagnostic thresholds

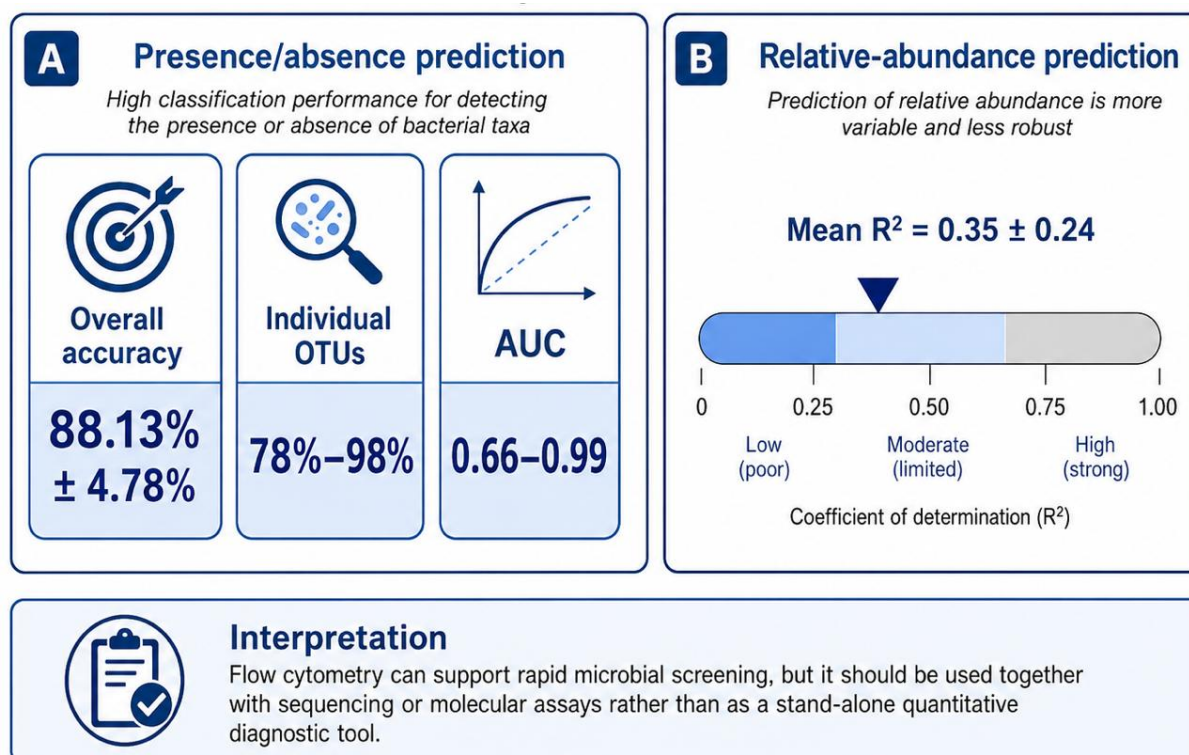
Indicator domain	Routine/healthy pattern	Alert or high-risk signal	Management interpretation and action
Target pathogens	Stable low background or non-detection	Repeated increase; virulence marker confirmed	Re-sample; confirm with qPCR/dPCR or culture; strengthen diagnostics and biosecurity
Community structure	Expected seasonal/developmental variation	Abrupt or persistent deviation from baseline	Increase monitoring; examine recent husbandry and environmental changes
Diversity/stability	Farm-specific normal range	Sudden loss of stability or resilience	Treat as supporting evidence, not diagnosis by itself
Health-associated taxa	Persistent baseline pattern	Repeated decline or disappearance	Examine concurrent stressors; avoid assuming causality without validation
Functional genes	Stable functional profile	Enrichment of virulence, stress, or resistance functions	Confirm target identity/activity; review antimicrobial and biosecurity history
Water quality	Expected operational range	Warming, hypoxia, nitrogen stress, organic loading	Correct manageable environmental stress and assess interaction with microbial signal
Host condition	Normal feeding, behavior and survival	Reduced feeding, lesions, abnormal behavior, increased mortality	Escalate clinical/pathogen diagnostics and targeted intervention

The value of the table is not the creation of fixed thresholds but the linkage of microbial evidence to progressively stronger actions. Such proportionality reduces two opposite errors: ignoring early ecological deterioration and overreacting to ordinary microbiome variability. Evidence from longitudinal aquaculture studies strongly supports this need for contextual rather than single-marker interpretation (Clinton et al., 2024; Lu et al., 2025).

6.5 Data-driven approaches for microbial risk prediction

Multivariate statistics and machine learning are well suited to microbial monitoring because the number of candidate microbial features often far exceeds the number of samples. Random forests, regularized regression, time-series models, and neural networks can combine taxa, cytometric features, environmental variables, and host measurements. Flow-cytometry research has already shown that microbial fingerprints contain enough structure to predict aspects of taxonomic composition, supporting their potential role in rapid screening (Heyse et al., 2021).

The main constraint is not algorithm availability but data quality. Models trained on one farm, season, or analytical pipeline may learn local signatures that fail elsewhere. Tank-level replication, independent validation, temporal testing, transparent feature selection, and calibrated uncertainty are therefore more important than model complexity. For current aquaculture applications, interpretable models that show why a sample was classified as risky may be more useful than opaque systems with marginally higher internal accuracy (Figure 2).



Data summarized from Heyse et al. (2021).

Figure 2 Performance of flow cytometry-based prediction of bacterial taxa in an aquaculture microbial community

7 Microbial Monitoring-Based Health Management Models for Marine Aquaculture

7.1 Routine microbial surveillance model

Routine surveillance begins by establishing what “normal” looks like. This requires repeated sampling during periods of acceptable production, covering major seasons, developmental stages, and management transitions. Baselines should include a manageable set of microbial measures-such as total cell counts, targeted pathogen abundance, community fingerprints, or periodic 16S profiles-alongside temperature, salinity, dissolved oxygen, nitrogen compounds, feeding, biomass, and health records.

Importantly, the baseline is a distribution, not a single reference sample. Longitudinal studies repeatedly demonstrate natural microbial succession in aquaculture systems (Kim et al., 2022; Bui et al., 2026). A farm that samples only during disease events has no reliable ecological reference against which to judge those events. Routine surveillance is therefore the foundation on which all later warning thresholds depend.

7.2 Microbial early-warning management model

Early-warning management focuses on deviation rather than diagnosis. A rapid monitoring tool might first identify an unusual cell-density pattern, pathogen increase, or community fingerprint. The result should then trigger confirmation using a more specific method and a simultaneous review of environmental and host data. This layered strategy balances speed with diagnostic reliability.

The approach is particularly attractive in hatcheries because microbial conditions can change quickly and early life stages are often vulnerable. Findings from oyster and barramundi larviculture suggest that community trajectories contain information related to later performance, although the predictive signals are not yet universal (Cram et al., 2024; Bui et al., 2026). Early warning should consequently be framed as increased probability requiring attention, not as certainty that disease will occur.

7.3 Risk-based intervention model

A risk-based model links intervention intensity to the weight of evidence. Low-risk conditions require routine husbandry; alert conditions justify increased sampling and correction of obvious environmental stress; high-risk conditions require focused diagnostic and biosecurity responses. Where intervention is necessary, management may include adjustment of feeding, aeration, water exchange, system hygiene, movement of animals, or other measures appropriate to the culture system.

This model also discourages prophylactic antimicrobial use based solely on a nonspecific microbial shift. Antimicrobials can themselves disrupt microbiomes, while responsible use is important for limiting resistance selection (Rosado et al., 2023). A microbiome-informed system should therefore reduce diagnostic uncertainty rather than create a new reason for indiscriminate treatment.

7.4 Microbiome regulation-based health management

Once a reproducible adverse microbial state has been identified, management can move beyond observation toward ecological regulation. Probiotics, prebiotics, synbiotics, biofloc management, and carefully selected microbial consortia are plausible tools for maintaining competitive microbial communities and improving host resilience. Evidence for *Phaeobacter* and other probiotic candidates shows that antagonism against pathogens can be harnessed, although effects remain strain- and system-dependent (Sonnenschein et al., 2021).

A more sophisticated goal is restoration of microbial function rather than introduction of one “beneficial” species. That idea remains ahead of current commercial evidence. Synthetic consortia, microbiota transplantation, and targeted microbiome engineering will require ecological and biosafety validation, especially in open marine systems where introduced microorganisms can interact with natural communities.

7.5 Adaptive and feedback-based health management

Health management becomes adaptive when monitoring does not end after intervention. Post-intervention samples should determine whether pathogen abundance decreased, microbial structure returned toward its normal range, environmental stress was corrected, and host condition improved.

7.6 Toward precision health management in marine aquaculture

Precision management requires thresholds that are specific enough to the farm to be meaningful but standardized enough to be transferable and audited. A practical future architecture may combine continuous environmental sensors with frequent low-cost microbial screening, less frequent sequencing for baseline renewal, and targeted molecular assays when warning signals appear.

Such a system does not require sequencing every sample. Indeed, an economically realistic workflow may use high-information technologies during discovery, then translate validated biomarkers into qPCR, dPCR, flow-cytometric, or biosensor assays. The recent development of field-oriented LAMP and rapid microbial fingerprinting supports this two-stage model of discovery followed by operational simplification (Pu et al., 2026; Bui et al., 2026).

8 Applications Across Major Marine Aquaculture Systems

8.1 Marine finfish aquaculture

Finfish provide multiple microbiome compartments for health monitoring, including water, gut, gills, skin, and mucus. External mucosae are particularly informative because they directly experience environmental change while functioning as barriers to infection. In marine-stage Atlantic salmon, specific gill-associated taxa correlated with gill-health status over a year-long production cycle, although general diversity metrics were not sufficient to define health (Clinton et al., 2024).

Gilthead seabream research also demonstrates that infection and antimicrobial treatment can affect different mucosal microbiomes in distinct ways (Rosado et al., 2023). Marine finfish monitoring should therefore avoid assuming that gut samples alone represent whole-animal microbial health. A tissue-specific sampling strategy is more defensible when the disease of interest has a defined portal of entry or mucosal target.

8.2 Shrimp aquaculture

Shrimp farming is particularly suited to microbial surveillance because animals and environmental microorganisms are closely connected through water, sediment, feed, fecal material, and the intestinal tract. Studies in *L. vannamei* have documented developmental changes in intestinal microbiota, salinity-associated restructuring, disease-related dysbiosis, and microbial differences among clear-water, probiotic, and biofloc production approaches (Deris et al., 2022; Vinay et al., 2022; Waiho et al., 2023).

Vibrio monitoring remains important, but its interpretation should extend beyond total relative abundance. Species, virulence potential, absolute load, environmental stress, and broader community structure provide a more defensible assessment. Shrimp studies of dysbiosis also show why community-level signals may complement rather than replace specific pathogen testing (Huang et al., 2020).

8.3 Shellfish aquaculture

Shellfish hatcheries illustrate both the promise and difficulty of microbial prediction. Larval cultures can undergo rapid production failure, yet potential pathogens may not always be the primary trigger. Cram et al. (2024) found that early microbial-community patterns in oyster larvae were related to later batch outcomes, while several organisms enriched during crashes likely took advantage of already deteriorating conditions.

Pacific oyster mortality syndrome provides a further example of complex disease ecology in which viral infection, bacterial communities, host susceptibility, and environment interact. Experimental work has associated microbiota composition with different disease outcomes, supporting the idea that shellfish health may need to be understood as a pathobiome rather than a one-pathogen system (Delisle et al., 2022).

8.4 Recirculating and high-density marine aquaculture systems

Engineered systems provide unusually strong opportunities for microbial health management because water flows, biofilters, aeration, disinfection, and feeding are more controllable than in open-water culture. They also create complex microbial connectivity among water, biofilms, filters, and animal mucosae. Temporal Atlantic salmon RAS research demonstrates that substantial microbial restructuring can occur even in highly controlled production environments (Lorgen-Ritchie et al., 2022).

This controllability makes RAS suitable for testing causal management interventions. When a microbial warning appears, managers can modify operational variables and observe subsequent microbial responses. Over time, such feedback-rich systems could become test beds for validating health indicators before similar concepts are transferred to less controllable cage or coastal farms.

9 Challenges and Future Perspectives

9.1 Lack of standardized microbial health indicators

The largest conceptual obstacle is the absence of a universal microbial definition of health. Species identity, developmental stage, diet, tissue, salinity, geographic location, season, and farm design all influence microbiome composition. Reviews of aquaculture dysbiosis consistently find recurring patterns, such as pathogen enrichment and community restructuring, but not a single taxonomic profile that defines healthy fish across systems (Mougin and Joyce, 2023; Xavier et al., 2024).

Standardization should therefore focus first on measurement and interpretation rather than universal taxa. Comparable sampling procedures, metadata, controls, sequence processing, absolute abundance measurements, and outcome definitions would make it easier to identify indicators that genuinely transfer across farms.

9.2 Relative abundance versus absolute quantification

Amplicon sequencing is compositional. If one organism expands strongly, the apparent relative abundance of all other organisms may decline even when their absolute cell numbers remain unchanged. This makes relative abundance alone potentially misleading for health decisions.

Combining community sequencing with total-cell measurements, spike-in standards, qPCR, or digital PCR can address part of this problem. Digital PCR is particularly attractive for operational biomarkers because it provides absolute target quantification, while viability treatments can further distinguish viable-cell signals in some applications (Yang et al., 2023). Future health indices should report absolute microbial loads whenever the biological question concerns infection pressure rather than community composition alone.

9.3 From association to causality

A dysbiotic microbiome may be a cause of disease, a consequence of disease, or a correlated response to the same environmental stressor. Distinguishing these possibilities requires temporal and experimental evidence. Shrimp research using microbiota manipulation has provided unusually strong evidence that dysbiosis can contribute to disease processes, but such causal demonstrations remain far less common than cross-sectional associations (Huang et al., 2020).

Future biomarker development should therefore proceed in stages: longitudinal association, independent replication, mechanistic testing, and finally prospective prediction. Organisms identified only because they dominate moribund animals should not be promoted immediately as early-warning biomarkers.

9.4 Need for long-term and multi-farm monitoring

A model that performs well on samples from one farm may simply recognize that farm. Seasonal patterns can create the same problem: an algorithm may inadvertently learn sampling date rather than disease risk. The Sanggou Bay study demonstrates how strong seasonality can be relative to culture-mode effects, while barramundi hatchery observations reveal persistent differences among tanks managed within the same facility (Lu et al., 2025; Bui et al., 2026).

Robust validation therefore requires several production cycles, multiple farms, independent cohorts, and deliberately separated training and test data. Shared longitudinal datasets linking microbiomes with environmental variables and standardized health outcomes would probably advance the field more than increasingly complex algorithms trained on small local datasets.

9.5 Standardization and cost reduction

Differences in filtration volume, sample storage, DNA extraction, primer choice, sequencing depth, bioinformatic pipelines, and taxonomic databases can all change the apparent microbiome. Operational monitoring adds further constraints: methods must be fast, reproducible, affordable, and usable by non-specialist personnel.

One realistic route is a two-tier technology system. Research laboratories could use sequencing and multi-omics to discover and validate indicators, while farms employ simplified qPCR, dPCR, flow-cytometry, LAMP, or biosensor

panels. The emergence of direct LAMP workflows for shrimp-culture water illustrates how eliminating complex DNA extraction can materially improve field practicality (Pu et al., 2026).

9.6 Integration of multi-omics, artificial intelligence, and smart aquaculture

The strongest future prediction systems are likely to combine microbial and non-microbial data. Environmental sensors can continuously measure variables such as temperature, dissolved oxygen, pH, and salinity, whereas microbial sampling provides biological information that sensors cannot. Multi-omics can identify functionally meaningful features, and machine learning can integrate heterogeneous variables across time.

The risk is technological excess. More variables and more complex models do not guarantee better management. Flow-cytometry studies demonstrate both the promise and limits of data-driven microbial fingerprints: community information can be predicted rapidly, but accuracy differs among taxa and tasks (Heyse et al., 2021). Future smart-aquaculture systems should therefore prioritize external validation, interpretability, uncertainty estimates, and actionable outputs over algorithmic novelty.

9.7 From microbial monitoring to microbiome management

The long-term direction of the field is a transition from observing microbial communities to deliberately maintaining desirable ecological functions. In the near term, this means avoiding unnecessary disturbance, maintaining stable environmental conditions, using validated probiotics where appropriate, and recognizing microbial deterioration before clinical disease. More advanced interventions may eventually include precision probiotics, defined microbial consortia, phage-based strategies, and ecological engineering of water and biofilms.

That transition should remain evidence-led. Marine aquaculture systems are connected to wider coastal ecosystems, so interventions that alter microbial communities may have consequences beyond the farm boundary. The most defensible health-management model is therefore not one that attempts to control every microorganism, but one that combines surveillance, ecological understanding, proportional intervention, and learning from repeated production cycles. In this framework, the practical endpoint of microbial monitoring is neither sequencing nor pathogen enumeration. It is better timing of management: recognizing instability while it is still reversible, confirming risk before acting, and evaluating whether intervention restores both animal health and microbial resilience.

References

- Bui N.M.N., Defoirdt T., Boon N., and Props R., 2026, Tracking microbial community dynamics in commercial barramundi larviculture: Insights from flow cytometry and 16S rRNA gene sequencing, *Aquaculture Reports*, 48: 103640.
<https://doi.org/10.1016/j.aqrep.2026.103640>
- Clinton M., Wyness A.J., Martin S.A.M., Brierley A.S., and Ferrier D.E.K., 2024, Association of microbial community structure with gill disease in marine-stage farmed Atlantic salmon (*Salmo salar*): A yearlong study, *BMC Veterinary Research*, 20(1): 340.
<https://doi.org/10.1186/s12917-024-04125-5>
- Cram J.A., McCarty A.J., Willey S.M., and Alexander S.T., 2024, Microbial community structure variability over the development of healthy and underperforming oyster larval hatchery broods, *Frontiers in Aquaculture*, 3: 1427405.
<https://doi.org/10.3389/faq.2024.1427405>
- Delisle L., Laroche O., Hilton Z., Burguin J.-F., Rolton A., Berry J., Pochon X., Boudry P., and Vignier J., 2022, Understanding the dynamic of POMS infection and the role of microbiota composition in the survival of Pacific oysters, *Crassostrea gigas*, *Microbiology Spectrum*, 10(6): e01959-22.
<https://doi.org/10.1128/spectrum.01959-22>
- Deris Z.M., Iehata S., Gan H.M., Ikhwannuddin M., Najiah M., Asaduzzaman M., Wang M., Liang Y., Danish-Daniel M., Sung Y.Y., and Wong W.L., 2022, Understanding the effects of salinity and *Vibrio harveyi* on the gut microbiota profiles of *Litopenaeus vannamei*, *Frontiers in Marine Science*, 9: 974217.
<https://doi.org/10.3389/fmars.2022.974217>
- Duan Y., Xing Y., Zeng S., Dan X., Mo Z., Zhang J., and Li Y., 2022, Integration of metagenomic and metabolomic insights into the effects of microcystin-LR on intestinal microbiota of *Litopenaeus vannamei*, *Frontiers in Microbiology*, 13: 994188.
<https://doi.org/10.3389/fmicb.2022.994188>
- Garibay-Valdez E., Cicala F., Martinez-Porchas M., Gómez-Reyes R., Vargas-Albores F., Gollas-Galván T., Martínez-Córdova L.R., and Calderón K., 2021, Longitudinal variations in the gastrointestinal microbiome of the white shrimp, *Litopenaeus vannamei*, *PeerJ*, 9: e11827.
<https://doi.org/10.7717/peerj.11827>

- Heyse J., Schattenberg F., Rubbens P., Müller S., Waegeman W., Boon N., and Props R., 2021, Predicting the presence and abundance of bacterial taxa in environmental communities through flow cytometric fingerprinting, *MSystems*, 6(5): e00551-21.
<https://doi.org/10.1128/msystems.00551-21>
- Huang Z., Zeng S., Xiong J., Hou D., Zhou R., Xing C., Wei D., Deng X., Yu L., Wang H., Deng Z., Weng S., Satapornvanit K., Ning D., Zhou J., and He J., 2020, Microecological Koch's postulates reveal that intestinal microbiota dysbiosis contributes to shrimp white feces syndrome, *Microbiome*, 8(1): 32.
<https://doi.org/10.1186/s40168-020-00802-3>
- Infante Villamil S., Huerlimann R., and Jerry D.R., 2021, Microbiome diversity and dysbiosis in aquaculture, *Reviews in Aquaculture*, 13(2): 1077-1096.
<https://doi.org/10.1111/raq.12513>
- Kim S.-K., Song J., Rajeev M., Kim S.K., Kang I., Jang I.-K., and Cho J.-C., 2022, Exploring bacterioplankton communities and their temporal dynamics in the rearing water of a biofloc-based shrimp (*Litopenaeus vannamei*) aquaculture system, *Frontiers in Microbiology*, 13: 995699.
<https://doi.org/10.3389/fmicb.2022.995699>
- Liu Z., Wang P., Li J., Luo X., Zhang Y., Huang X., Zhang X., Li W., and Qin Q., 2024, Comparative metagenomic analysis of microbial community compositions and functions in cage aquaculture and its nearby non-aquaculture environments, *Frontiers in Microbiology*, 15: 1398005.
<https://doi.org/10.3389/fmicb.2024.1398005>
- Lorgen-Ritchie M., Clarkson M., Chalmers L., Taylor J.F., Migaud H., and Martin S.A.M., 2022, Temporal changes in skin and gill microbiomes of Atlantic salmon in a recirculating aquaculture system-Why do they matter?, *Aquaculture*, 558: 738352.
<https://doi.org/10.1016/j.aquaculture.2022.738352>
- Lu L., Ni L., Ai C., Zhang D., Zheng P., Li X., Liu X., and Dang H., 2025, Seasonal dynamics of microbial communities link to summer-autumn aquaculture disease outbreaks in Sanggou Bay, *Frontiers in Marine Science*, 12: 1581190.
<https://doi.org/10.3389/fmars.2025.1581190>
- Mougin J., and Joyce A., 2023, Fish disease prevention via microbial dysbiosis-associated biomarkers in aquaculture, *Reviews in Aquaculture*, 15(2): 579-594.
<https://doi.org/10.1111/raq.12745>
- Nababan Y.I., Yuhana M., Penataseputro T., Nasrullah H., Alimuddin, and Widanarni, 2022, Dietary supplementation of *Pseudoalteromonas piscicida* IUB and fructooligosaccharide enhance growth performance and protect the whiteleg shrimp (*Litopenaeus vannamei*) against WSSV and *Vibrio harveyi* coinfection, *Fish & Shellfish Immunology*, 131: 746-756.
<https://doi.org/10.1016/j.fsi.2022.10.047>
- Naylor R.L., Hardy R.W., Buschmann A.H., Bush S.R., Cao L., Klinger D.H., Little D.C., Lubchenco J., Shumway S.E., and Troell M., 2021, A 20-year retrospective review of global aquaculture, *Nature*, 591(7851): 551-563.
<https://doi.org/10.1038/s41586-021-03308-6>
- Pu X., Lu F., Yang Q., Han Z., Zhu X., Chen J., Zhang D., and Zhang X., 2026, Direct LAMP for on-site rapid detection of *Vibrio parahaemolyticus* in shrimp (*Litopenaeus vannamei*) aquaculture water, *PLoS ONE*, 21(4): e0348231.
<https://doi.org/10.1371/journal.pone.0348231>
- Rahman A.M.A., Ransangan J., and Subbiah V.K., 2022, Improvements to the rapid detection of the marine pathogenic bacterium, *Vibrio harveyi*, using loop-mediated isothermal amplification (LAMP) in combination with SYBR Green, *Microorganisms*, 10(12): 2346.
<https://doi.org/10.3390/microorganisms10122346>
- Rosado D., Canada P., Silva S.M., Ribeiro N., Diniz P., and Xavier R., 2023, Disruption of the skin, gill, and gut mucosae microbiome of gilthead seabream fingerlings after bacterial infection and antibiotic treatment, *FEMS Microbes*, 4: xtad011.
<https://doi.org/10.1093/femsmc/xtad011>
- Sonnenschein E.C., Jimenez G., Castex M., and Gram L., 2021, The *Roseobacter*-group bacterium *Phaeobacter* as a safe probiotic solution for aquaculture, *Applied and Environmental Microbiology*, 87(5): e02581-20.
<https://doi.org/10.1128/AEM.02581-20>
- Vinay T.N., Patil P.K., Aravind R., Shyne Anand P.S., Baskaran V., and Balasubramanian C.P., 2022, Microbial community composition associated with early developmental stages of the Indian white shrimp, *Penaeus indicus*, *Molecular Genetics and Genomics*, 297(2): 495-505.
<https://doi.org/10.1007/s00438-022-01865-7>
- Waiho K., Abd Razak M.S., Abdul Rahman M.Z., Zaid Z., Ikhwannuddin M., Fazhan H., Shu-Chien A.C., Lau N.-S., Azmie G., Ishak A.N., Syahnon M., and Kanan N.A., 2023, A metagenomic comparison of clearwater, probiotic, and Rapid BFT™ on Pacific whiteleg shrimp, *Litopenaeus vannamei* cultures, *PeerJ*, 11: e15758.
<https://doi.org/10.7717/peerj.15758>
- Xavier R., Severino R., and Silva S.M., 2024, Signatures of dysbiosis in fish microbiomes in the context of aquaculture, *Reviews in Aquaculture*, 16(2): 706-731.
<https://doi.org/10.1111/raq.12862>
- Yajima D., Fujita H., Hayashi I., Shima G., Suzuki K., and Toju H., 2023, Core species and interactions prominent in fish-associated microbiome dynamics, *Microbiome*, 11(1): 53.
<https://doi.org/10.1186/s40168-023-01498-x>
- Yang J., Xu H., Ke Z., Kan N., Zheng E., Qiu Y., and Huang M., 2023, Absolute quantification of viable *Vibrio cholerae* in seawater samples using multiplex droplet digital PCR combined with propidium monoazide, *Frontiers in Microbiology*, 14: 1149981.
<https://doi.org/10.3389/fmicb.2023.1149981>

Zhao R., Symonds J.E., Walker S.P., Steiner K., Carter C.G., Bowman J.P., and Nowak B.F., 2023, Relationship between gut microbiota and Chinook salmon (*Oncorhynchus tshawytscha*) health and growth performance in freshwater recirculating aquaculture systems, *Frontiers in Microbiology*, 14: 1065823.
<https://doi.org/10.3389/fmicb.2023.1065823>



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