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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.

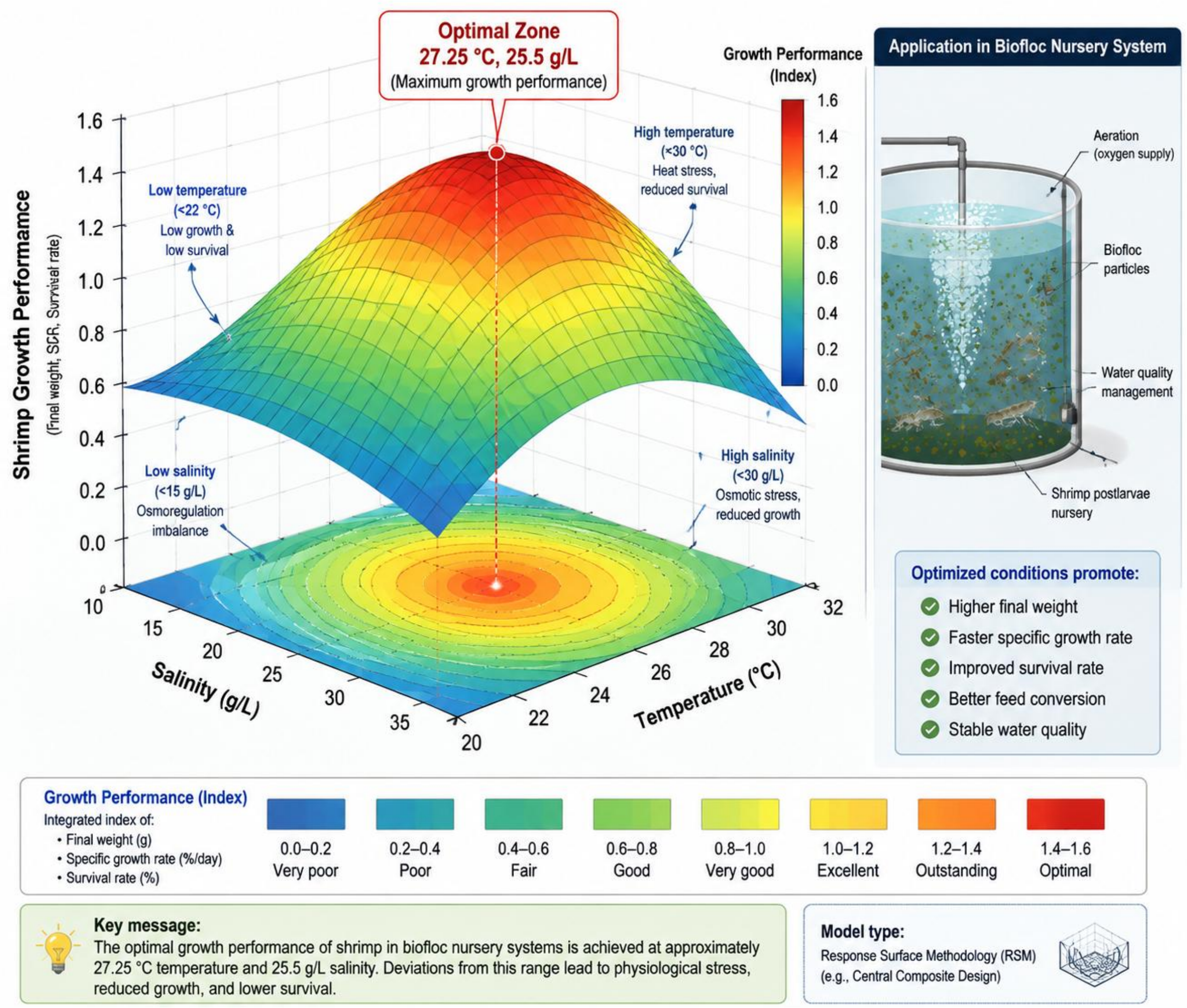

Figure 1 Response surface optimization of shrimp growth performance under different temperature and salinity combinations in intensive nursery systems. The three-dimensional model illustrates the interaction between temperature and salinity and identifies the optimal environmental zone for maximizing 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 × temperature interaction significantly influenced all three growth indices (Li et al., 2024).

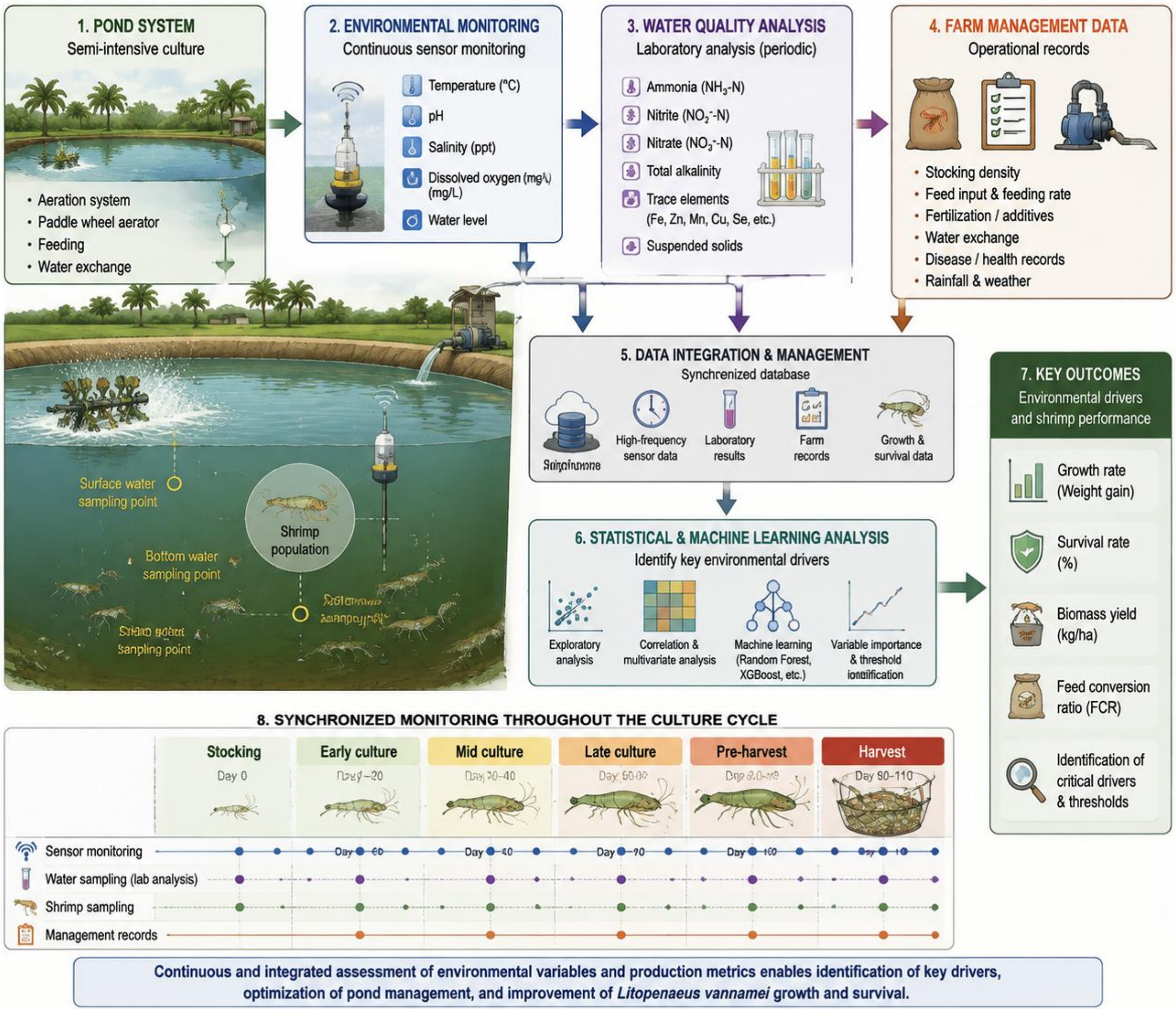

Figure 2 Integrated environmental monitoring framework for identifying environmental drivers of *Litopenaeus vannamei* growth and survival in pond aquaculture systems

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.

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