

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).