

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.