

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.