serve as practical predictors when direct physiological measurements are not available (Erniati et al., 2023; Koç and Kayra, 2024). In watermelon, light interception, total solar radiation per plant, and photosynthetic production are closely correlated with fruit weight in vertically trained systems, indicating that radiation-related variables (incident radiation, intercepted PAR, or canopy light-use indices) are key environmental drivers to incorporate in fruit weight models (Gao et al., 2023).

Process-based models require additional internal state variables to link environment to growth. Biophysical fruit models commonly track water content, dry matter, sugar concentrations in fruit and phloem, turgor pressure, transpiration and respiration rates, and xylem-phloem flows, using hourly atmospheric inputs (temperature, humidity) as boundary conditions. Integrated plant-fruit models further include indicators of source-sink balance, such as sucrose concentration in the phloem, stem water potential, and measures of water and nitrogen status, linking these to fruit mass via functions that modify assimilate supply or hydraulic conductance under stress (Zhou et al., 2025).

5.3 Establishment and mathematical expression of dynamic models for watermelon fruit weight

Dynamic modeling of watermelon fruit weight can draw from established formulations in fruit growth modeling. Biophysical approaches treat the fruit as a compartment with state variables for water (w) and dry matter (s), and describe fluxes of water and sugar between fruit, plant, and atmosphere using mass-balance differential equations; sugar uptake is partitioned among mass flow, passive diffusion, and active transport, while cell wall expansion is driven by turgor according to irreversible growth equations at the tissue scale. Such models express fresh mass as the sum of water and dry matter, driven by environmental inputs (temperature, humidity) and plant water status, thereby enabling simulation of diurnal swelling-shrinkage cycles and seasonal growth trajectories that could be adapted to watermelon fruits.

More recent frameworks integrate cellular processes (cell division and expansion), resource limitation, and hormone signaling into compact mathematical structures. A minimal cell-expansion-division model represents temporal changes in cell number and mean cell mass under constraints of carbon and water supply, producing emergent dynamics of total fruit mass and cell size distributions that match observations across genotypes and environments (Miele et al., 2025). Likewise, process-based models that link carbon and water fluxes to endogenous ABA include sub-models for sugar uptake, respiration, hydraulic conductance, and transpiration modulated by ABA concentration, allowing simulation of fruit mass under variable temperature and water availability (Chung et al., 2025). By calibrating such differential-equation systems with watermelon-specific environmental data and fruit growth measurements, dynamic models can be formulated that quantitatively relate environmental factors and physiological indicators to the time course of watermelon fruit weight.

6 Validation and Evaluation of Watermelon Fruit Weight Models

6.1 Evaluation of the fitting accuracy of watermelon fruit weight prediction models

Assessing model accuracy is central to evaluating watermelon fruit weight prediction, and most recent work relies on statistical indices such as root mean squared error (RMSE) and coefficient of determination (R^2). In a non-destructive image-based system for spherical fruits, including watermelon, U-Net segmentation extracted geometric ratios from images and several regression models were trained; performance was evaluated using MSE, MAE, RMSE, and R^2, allowing direct comparison of model fits across algorithms. For watermelon, Random Forest and Decision Tree models showed the highest training success, achieving an R^2 of 0.9112 in the best case, whereas linear and SGD models performed poorly, illustrating the value of non-linear models when fruit appearance and weight relationships are complex (Koç and Kayra, 2024).

Similar criteria are widely adopted in other fruit weight modeling studies and provide a benchmark for what constitutes an acceptable fit. For example, a machine-learning framework for non-destructive plum fruit weight estimation compared SVR, MLR, MLP, and Decision Tree models using RMSE and R^2 in both training and testing, selecting the optimal structure based on lowest RMSE and highest R^2. The best SVR model reached training R^2 of 0.9369 with RMSE 0.4850 g and test R^2 of 0.9267, confirming that accurate fresh-weight models can be obtained when evaluation is rigorously based on these metrics and when training-testing separation is respected to avoid overfitting (Sabouri et al., 2025).