regulator combinations to detect treatments that raise both yield and Brix (Correa et al., 2020; Raj et al., 2022). Biomass-related traits such as shoot and fruit dry mass, harvest index, and partitioning between vegetative and reproductive organs are collected in source-sink experiments to describe how pruning and fruit number modify photoassimilate allocation and fruit size (Deka et al., 2024).

4.3 Processing and quality control of environmental monitoring data for watermelon

Environmental monitoring is crucial for interpreting treatment effects on fruit weight and for parameterizing environmental-response models. In field and protected experiments, weather data (air temperature, radiation, and sometimes humidity) are commonly obtained from nearby meteorological services or on-site stations to describe seasonal conditions and compare sowing dates or density treatments under similar macroclimates (Gao et al., 2023). Soil moisture is monitored directly in mulching or irrigation studies, where mulched plots generally maintain higher moisture and reduced weed competition than bare-soil controls, supporting higher single-fruit weight and total yield (Yismaw et al., 2024). In subsurface fertigation systems, spacing relative to the irrigation source is explicitly tested, and treatment differences in plant growth and fruit weight are interpreted in light of soil type and the distance from clay pot emitters (Sutarno et al., 2022).

Quality control of environmental data focuses on ensuring consistency, representativeness, and correct linkage to plot-level observations. Experiments using mulches or subsurface irrigation typically collect repeated measurements of soil moisture and sometimes weed biomass, enabling cross-checks between moisture trends and yield responses across treatments (Sutarno et al., 2022; Yismaw et al., 2024). When studying seasonal or sowing-date effects, growth and yield measurements at 60-120 days after sowing are evaluated together with environmental records to identify the sowing window that aligns with favorable temperature and radiation, resulting in superior fruit set, fruit weight, yield per hectare, and Brix (Kim et al., 2023; Bora et al., 2024). Such careful integration of environmental and yield datasets underpins robust inferences about how temperature, light, and moisture regimes drive variation in watermelon fruit weight and related quality traits.

5 Methods for Constructing Watermelon Fruit Weight Models

5.1 Model types applicable to watermelon fruit weight prediction

Empirical models predict fruit weight directly from observable traits or management factors without explicitly representing underlying physiology. For watermelon and other spherical fruits, non-destructive image features (segmented area, bounding box ratios) have been coupled with machine-learning regressors such as Random Forest and Decision Trees to predict individual fruit weight with high accuracy, demonstrating the power of purely data-driven approaches when sufficient labeled images are available (Koç and Kayra, 2024). In agronomic optimization, multiple linear or polynomial regression has been used to relate watermelon fruit weight to input factors such as poultry, cow, and goat manure rates within a Simplex Lattice Design framework, yielding statistically significant quadratic response surfaces for fruit weight and fruit number per plant (Sabouri et al., 2025).

Mechanistic and process-based models, by contrast, attempt to represent fruit growth as the outcome of carbon and water transport, cell expansion, and environmental drivers over time. Biophysical models of fruit such as the virtual-fruit framework describe water and dry-matter flows via xylem and phloem, osmotic and turgor pressures, and cell wall extension, and are capable of simulating seasonal and diurnal dynamics of fruit fresh and dry mass under varying crop load and water status. More recent integrative models explicitly couple carbon and water fluxes with hormonal regulation (e.g., abscisic acid) to simulate fruit mass and its response to heat, cold, and drought, illustrating how mechanistic structures can capture environmental regulation and stress-induced delays in growth in a way that empirical models cannot (Chung et al., 2025).

5.2 Selection of variables influencing watermelon fruit weight

A critical step in model construction is selecting environmental variables that strongly influence watermelon fruit growth. For empirical prediction in other cucurbits, fruit age, harvest date, plant height, fruit length and width, flesh thickness, cavity diameter, branch number, and leaf number have been used as ANN inputs, achieving high determination coefficients for fruit weight, which suggests that morphological and phenological descriptors can