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Modeling Fruit Weight Formation in Watermelon Based on Environmental Factors

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Abstract Watermelon (*Citrullus lanatus*) fruit weight is a crucial indicator for assessing both yield and commercial value, and it is subject to the combined influence of various environmental factors. To elucidate the regulatory mechanisms by which environmental factors govern watermelon fruit weight formation, this study-grounded in the biological processes of fruit development — systematically analyzed the impact patterns of key environmental variables (including temperature, light, water, and soil nutrients) on fruit expansion and dry matter accumulation. Building upon this foundation, field experiments were conducted across multiple environmental settings to acquire data on watermelon fruit weight and related growth parameters; subsequently, utilizing a combination of statistical analysis and modeling techniques, a fruit weight formation model applicable to diverse cultivation conditions was constructed. The model was further employed to simulate and validate watermelon fruit weights under various ecological environments; the results demonstrated that the model possesses high predictive accuracy and stability, effectively capturing the dynamic responses of fruit weight formation to fluctuations in environmental factors. Furthermore, through case studies, the potential applications of the model in irrigation scheduling, fertilization management, and the optimization of controlled-environment cultivation systems were explored. The findings of this study provide a theoretical basis and technical support for achieving high-yield, high-quality watermelon cultivation, while also offering a valuable reference for the broader application and extension of fruit development models within the field of horticultural crops.
Keywords Watermelon (*Citrullus lanatus*); Fruit weight formation; Environmental factors; Model construction; Fruit development

1 Introduction

Watermelon is a major horticultural crop worldwide, valued for its large, fleshy fruits and high consumer demand, with millions of hectares under cultivation and China as the largest producer (Gao et al., 2023). Fruit size and weight are central components of yield and directly influence growers' income and market competitiveness. Industry-oriented studies and cultivar evaluations routinely use average fruit weight, fruit size distribution, and total yield as core performance indices, underlining fruit weight as a pivotal target for breeding, grafting, and agronomic management in commercial production systems (Jordana et al., 2023).

Beyond simple count of fruits, multiple analyses show that increases in total yield often arise mainly from higher average fruit weight rather than fruit number. Systematic review of grafted versus nongrafted watermelon demonstrates that grafting can raise total yield and average fruit weight by more than 10%-20%, highlighting fruit weight as the primary yield driver under diverse production conditions (Jordana et al., 2023). Field trials in different regions and seasons similarly evaluate cultivars and management practices using fruit weight, length, width, and fruit weight per plant, confirming their central role in rating economic performance and recommending cultivars to growers (Kumari et al., 2025). Management strategies such as optimizing flower retention or adjusting nitrogen and boron nutrition are explicitly aimed at maximizing individual fruit size and weight to achieve superior yield and quality (Gülüt, 2021).

At the biological level, fruit weight formation is determined by coordinated phases of cell division and cell expansion during early and mid-development. Early work on watermelon showed that after flowering, pollinated and hormone-induced parthenocarpic fruits undergo active cell proliferation in pericarp and ovule tissues, whereas unpollinated fruits rapidly cease growth, linking successful fruit set and early cell division to subsequent fresh weight accumulation. Broader studies in model species indicate that fruit development proceeds through fruit set, a growth phase dominated by cell division and then expansion, and maturation/ripening, all tightly regulated by phytohormones such as auxin and gibberellins (Fenn and Giovannoni, 2020). High-resolution analyses highlight that fertilization and seed-derived signals trigger a transition to cell expansion that drives post-fertilization fruit growth and final size, emphasizing that both cellular processes and hormonal regulation underpin fruit weight . In cucurbits and other fleshy fruits, early developmental windows are considered “critical periods” in which disturbances can irreversibly constrain final fruit size and yield potential (Gao et al., 2023).

Environmental factors strongly modulate these developmental processes, making research on their regulatory roles essential for understanding and predicting watermelon fruit weight. Light conditions, for example, have been shown to markedly alter fruit expansion: low-light or shading during 0-15 days after pollination reduces fruit size, soluble sugars, and amino acids, and affects expression of thousands of genes related to metabolism and transcriptional regulation in developing watermelon fruit. Greenhouse orientation and internal microclimate alter solar radiation, temperature, transpiration, and leaf gas exchange around the fruiting zone, which in turn influence fruit volume increase in seedless watermelon (Woo et al., 2022). Supplementary LED lighting and optimized temperature or nutrient regimes around the fruit set region significantly increase fruit mass, size, flesh thickness, and overall yield in plastic-house and winter or early-spring crops, highlighting light, temperature, and mineral availability as key environmental levers for fruit weight formation (Chamchum et al., 2023). Weather studies at field scale further show that precipitation and temperature patterns across seasons drive differences in yield and fruit quality, with drier seasons often associated with higher productivity (Bai et al., 2020).

Despite this growing body of work on environmental impacts, quantitative models that explicitly link dynamic environmental conditions to fruit weight formation in watermelon remain scarce. In other fruit and crop systems, nonlinear growth functions, Bayesian sigmoidal models, and process-based simulation models (e.g., modified WOFOST, SIMBA, or radial basis function neural networks) have been successfully used to describe fruit growth dynamics and predict yields based on time, physiological status, and environmental drivers. Such models capture characteristic sigmoidal or multi-phase growth curves and can integrate factors like temperature, radiation, and plant age to forecast final fruit weight or total yield with high accuracy. However, comparable modeling efforts tailored to watermelon, particularly under controlled-environment or protected cultivation where light, temperature, and supplemental energy inputs are actively managed, are largely absent. Given the demonstrated sensitivity of early fruit expansion and final fruit weight to radiation, temperature, and nutrient conditions in watermelon, there is a clear need to develop and validate models that mechanistically and quantitatively link environmental variables to fruit weight formation. Such models could support decision-making for greenhouse design and orientation, supplemental lighting strategies, temperature control regimes, and fertilization programs, enabling producers to optimize resource use while stabilizing or increasing yield and fruit quality under variable climatic and market conditions.

2 Biological Basis of Watermelon Fruit Weight Formation

2.1 Stages of watermelon fruit development

Watermelon fruit development proceeds through fruit set, a rapid expansion phase, and maturation, each characterized by distinct physiological and molecular changes. Early after pollination, rapid cell division in the young ovary and fruitlets establishes the basic cell number and tissue pattern, a phase tightly coordinated with ethylene- and hormone-related gene expression and high ethylene evolution in fruitlets (Anees et al., 2023). Following this, fruit growth switches to a prolonged cell expansion phase in which vacuolated parenchyma cells enlarge and accumulate sugars, pigments, and other solutes that drive osmotic water uptake and volume increase, forming the bulk of fruit flesh mass.

The expansion and maturation stages are marked by coordinated changes in gene expression and metabolites that define size, texture, color, and sweetness. Transcriptome and digital expression profiling across key developmental stages show thousands of differentially expressed genes related to cell wall metabolism, sugar accumulation, carotenoid biosynthesis, and stress and hormone signaling, all modulated as fruits pass from immature white to fully ripe red or over-ripe stages (Yu et al., 2022). Non-destructive and physiological measurements further indicate that ripening involves progressive pigment and carotenoid changes at the surface and within the flesh, along with hormone shifts typical of non-climacteric, ABA-and ethylene-modulated maturation, which together stabilize final fruit size and weight (Dhanani et al., 2022).

2.2 Mechanisms by which watermelon flesh cell division and expansion contribute to fruit weight

Fruit weight is fundamentally determined by the final number and size of flesh cells. In watermelon, cell division predominates during only the first several days after anthesis, followed by a long expansion phase in which existing cells enlarge dramatically through vacuolation and wall remodeling. Anatomical studies comparing pollinated, auxin-induced parthenocarpic, and unpollinated fruits show that early fruit growth depends on active cell division in pericarp and ovule tissues; unpollinated ovaries, which lack sustained division, rapidly cease growth, illustrating the centrality of early proliferative activity for subsequent fruit mass potential. After this brief proliferative window, increases in pulp weight from about one week onward are largely ascribed to cellular expansion, consistent with microscopic evidence that watermelon flesh cells become large and visually apparent as fruits enlarge (Kojima et al., 2020).

Cell expansion is driven by coordinated changes in cell wall architecture, hormonal signals, and metabolic status. Studies of firmness and texture reveal that differences in protopectin, cellulose, and hemicellulose contents, together with cell number, packing, and wall thickness, underlie variation in tissue density and mechanical support for expanding cells (Sun et al., 2020; Mashilo et al., 2022). Auxin- and Aux/IAA-mediated pathways modulate cell enlargement and the balance between cell size and number: high expression or allelic variants of Aux/IAA are linked to increased cell number, smaller cell size, and higher firmness, whereas reduced Aux/IAA activity is associated with larger cells and softer flesh, indicating that auxin signaling tunes the cellular composition that ultimately contributes to fruit volume and weight (Anees et al., 2023).

2.3 The impact of source-sink relationships in watermelon plants on fruit weight accumulation

Fruit growth depends on assimilate and water supply from vegetative organs, with the developing fruit acting as a strong sink whose demand changes across development. Dynamic sap-flow monitoring along fruit stalks across successive developmental stages shows that diurnal water distribution between leaves and fruit shifts markedly as fruits expand, slow growth, and reach maturity. During early expansion, nighttime inflow to the fruit dominates, correlating with rapid daily mass increase, whereas at later stages midday transpiration demand in leaves competes more strongly, shortening net inflow periods and reducing net fruit growth, before inflow and outflow balance at maturity when phenotype and weight stabilize (Zhang et al., 2024). Under low-light conditions, reduced photosynthesis and altered carbon and nitrogen metabolism associate with smaller fruits, lower soluble sugar and amino acid contents, and extensive transcriptional reprogramming, demonstrating that source capacity strongly constrains sink development during the critical 0-15 days after pollination expansion window (Gao et al., 2023).

Water supply and photosynthate partitioning also interact with environmental water availability and irrigation management to determine final fruit size and yield. Experiments manipulating drip irrigation at different fractions of crop water requirement across growth stages show that severe water deficits reduce total and marketable yield, average fruit weight, and fruit number, with vegetative growth and active fruit development phases more sensitive than the ripening phase. Deficit irrigation applied only during ripening has a comparatively smaller impact on marketable fruit weight and improves water-use efficiency, implying that the sink strength of fruits is highest and most vulnerable to water limitation during early and mid-development when rapid mass accumulation occurs. Together, these findings indicate that fruit weight formation in watermelon emerges from an integrated source-sink system, in which environmental factors such as light and water modulate assimilate production and transport to the fruit, thereby shaping the trajectory of fruit growth and final weight.

3 Key Environmental Factors Influencing Watermelon Fruit Weight

Watermelon fruit weight is shaped by a complex interaction of temperature, light, water, and nutrient status that together regulate cell division, cell expansion, and carbohydrate supply to developing fruits. Studies in protected and open-field systems show that modifying microclimate or resource availability around the fruiting zone can substantially alter fruit volume, sugars, and final yield per plant. Temperature and light, in particular, determine photosynthetic capacity and assimilate partitioning, while water and soil factors influence canopy function, root activity, and stress responses that indirectly affect fruit growth rates (Woo et al., 2022). Understanding these key environmental drivers is essential for building predictive models of fruit weight formation and for designing precise cultivation strategies in climate-vulnerable production regions (Barros et al., 2024).

3.1 The impact of temperature variations on watermelon fruit expansion rate and final fruit weight

Targeted heating around the fruiting region clearly demonstrates that temperature during early enlargement can accelerate fruit growth and increase final fruit weight. Raising the minimum temperature around fruit-bearing shoots to 18 °C in early spring plastic-house production significantly increased fresh fruit weight per plant, soluble solids, and fruit set rate, indicating enhanced sink activity and yield potential under suboptimal ambient conditions. High night-time temperature around young fruits (approximately 6 °C above the control) similarly increased fruit length, diameter, and weight by 16 days after anthesis through accelerated cell enlargement, even though final size at harvest later converged with the control (Chamchum et al., 2023).

The timing of temperature elevation also influences internal quality and sugar accumulation associated with fruit weight formation. Heating the fruit and nearby shoots during the early cell enlargement stage (5-20 days after anthesis) increased sucrose phosphate synthase activity and led to higher sucrose content at maturity, particularly in outer flesh tissues, suggesting that warm conditions can promote both structural growth and assimilate storage capacity. When high-temperature treatments were imposed between 10 and 20 days after anthesis, cell enlargement in the central region was stimulated and sugar contents at harvest generally increased; by contrast, high temperatures applied only after 20 days enhanced cell expansion in peripheral tissues but reduced sugar levels overall, indicating that late heat can impair optimal sugar accumulation while still altering fruit morphology.

3.2 The role of light conditions in the accumulation of watermelon photosynthetic products and fruit weight formation

Light intensity and spectral composition strongly control photosynthetic production and distribution of assimilates to fruits, thereby determining fruit size. In vertically trained, high-density systems, increasing shading with planting density reduced per-plant solar radiation interception and whole-plant photosynthetic production, which was closely correlated with reduced fruit size despite little change in soluble solids, highlighting light-driven assimilate supply as a primary determinant of fruit weight. Experiments on greenhouse orientation showed that a southeast-northwest single-span greenhouse received higher integrated solar radiation and higher leaf transpiration near fruits than an east-west structure, and these microclimatic differences were associated with increased fruit volume expansion in seedless watermelon (Figure 1) (Woo et al., 2022).

Artificial supplemental lighting further illustrates the role of light in driving both biomass production and carbohydrate accumulation in fruits. In winter-grown watermelon, evening LED lighting at 900 μmol m^{-2} s^{-1} significantly increased chlorophyll content, photosynthetic rate, fruit number, fruit weight, and flesh thickness, leading to a 31% yield increase and higher fruit sugar content relative to natural-light controls (Hossain et al., 2025). Similarly, plastic-house plants receiving 6-12 h of white LED light at night produced heavier fruits with larger dimensions and thicker flesh than non-supplemented plants, confirming that extended photoperiod and elevated photon flux enhance fruit growth by bolstering daily carbon gain and translocation to reproductive sinks (Gao et al., 2023).

3.3 Regulatory mechanisms of water and soil nutrients on watermelon fruit weight formation

Water availability and root-soil interactions regulate canopy temperature, photosynthesis, and stress physiology, which in turn shape fruit development and final weight. Experiments manipulating the wetted soil area under drip irrigation (12%-22% of surface) in semi-arid Brazil showed that average leaf temperature remained below air temperature and that fruit mass and BRIX were statistically similar across treatments, suggesting that a relatively wide range of localized wetting can maintain physiological stability and high yield if overall water supply is adequate (Barros et al., 2024). Under drought, however, arbuscular mycorrhizal colonization improved root development, protected chloroplast ultrastructure, and maintained higher photosynthetic efficiency, leading to better water status and greater accumulation of soluble sugars and osmolytes, mechanisms that support sustained assimilate delivery to developing fruits under water-limited conditions.

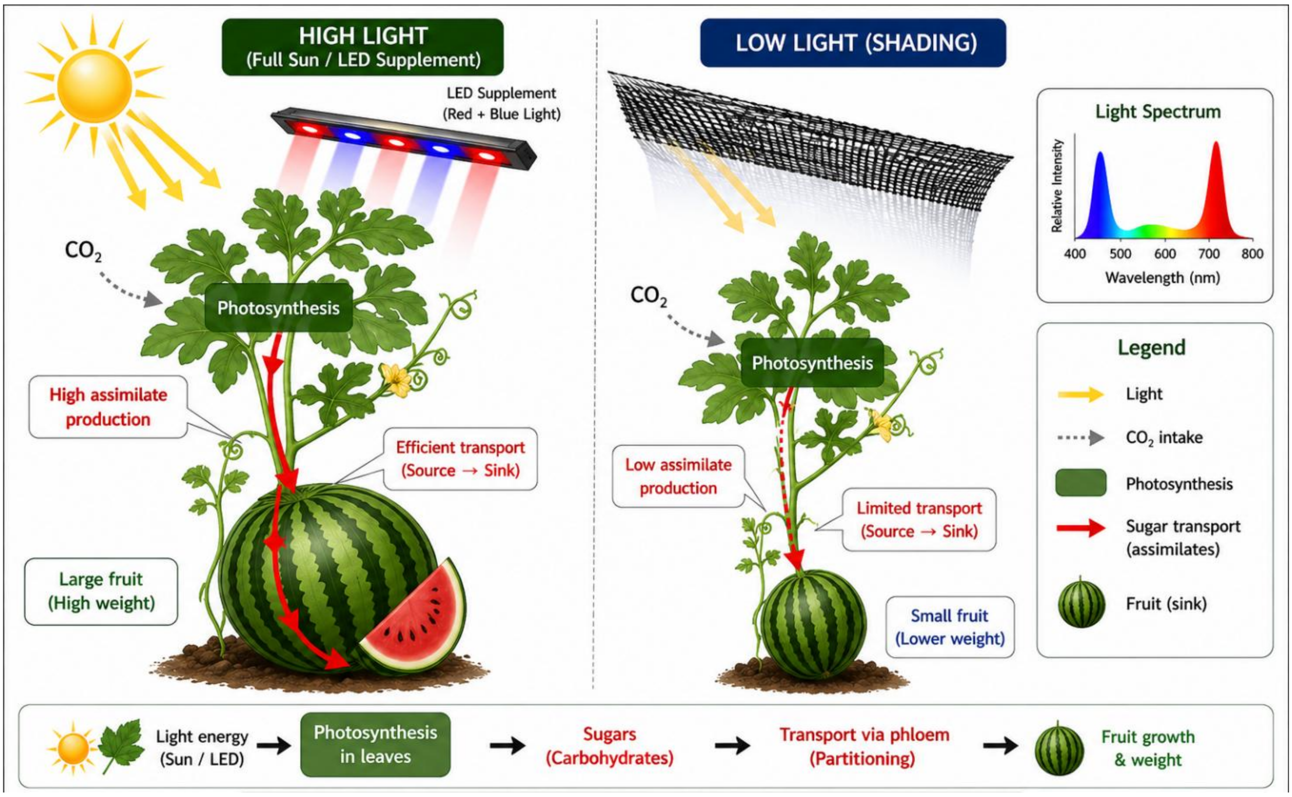

Figure 1 Role of light intensity and spectral quality in regulating photosynthetic carbon assimilation and its allocation to watermelon fruits. Increased light availability enhances assimilate supply and promotes fruit growth and weight formation

Soil nutrient status, particularly calcium and magnesium around the fruit set region, further modulates fruit growth and quality. Heating treatments at 18 °C near the fruiting zone not only increased fruit weight and soluble solids but were accompanied by elevated Ca^{2+} and Mg^{2+} concentrations in leaves adjacent to the fruit set node, implying improved nutrient uptake and transport under optimized temperature, which likely stabilizes cell wall structure and photosynthetic function during critical phases of fruit expansion. Supplemental LED lighting in winter crops likewise increased Ca^{2+} and Mg^{2+} in leaves at the fruit set region, enhancing photosynthetic rates and supporting consistent plant growth, which translated into larger fruit size, thicker flesh, and higher sugars, indicating tight coupling between nutrient status, carbon assimilation, and fruit weight formation under low-light, cool-season conditions (Hossain et al., 2025).

4 Data Acquisition and Experimental Design for Watermelon Fruit Weight Research

4.1 Design of watermelon field experiments

Field experiments on watermelon fruit weight are typically structured as factorial randomized or randomized block designs to evaluate genetic and management factors simultaneously. Representative studies select two or more commercial cultivars differing in fruit size class or adaptation, such as ‘Crimson Sweet’, ‘Sugar Baby’, or locally important hybrids, and test them across multiple locations or seasons to account for environmental variation. Treatments often include mulching materials, fertilizer regimes, or pruning and fruit-thinning levels, arranged with three or more replications to enable analysis of variance and proper error estimation (Deka et al., 2024). This design supports estimation of main and interaction effects on average fruit weight and yield components, while maintaining uniform baseline agronomic practices such as irrigation and pest management across plots (Yismaw et al., 2024).

Planting density is a central experimental factor because it simultaneously affects resource competition, canopy structure, and marketable fruit size. Trials commonly compare several inter- and intra-row spacings (for example, 3.0 × 0.8 m vs. 2.0 × 0.6 m, or 120 × 60 cm vs. denser arrangements) to quantify responses of fruit number, average fruit weight, commercial fruit proportion, and total yield per hectare (Silva et al., 2021). In some studies, plant density is integrated with training system (horizontal vs. vertical), stem number, or fruit-thinning treatments to manipulate source-sink balance and define optimal load per plant for targeted fruit-size categories (Kim et al., 2023). Such multifactor designs allow identification of densities that maximize total yield without excessively shifting the population toward undersized or mini fruits, while preserving desirable quality traits such as soluble solids content (Figure 2) (Tegen et al., 2021).

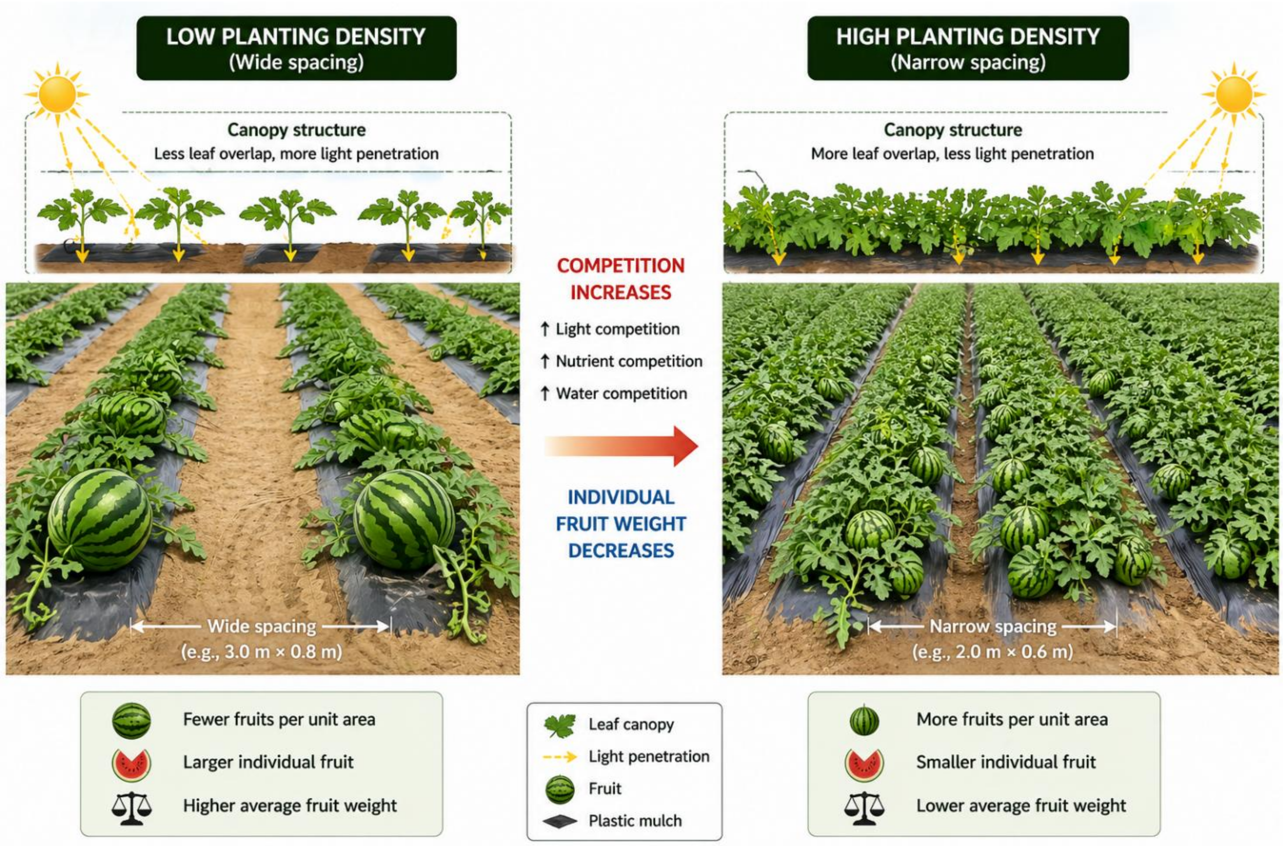

Figure 2 Effect of planting density on the trade-off between fruit number and individual fruit weight in watermelon production systems

4.2 Collection of data on watermelon fruit weight and related growth indicators

Fruit weight is usually recorded at harvest as single-fruit weight and/or average fruit weight per plant or per plot, along with fruit number to derive total and marketable yields. Detailed datasets often include fruit length, fruit diameter, average fruit weight, and total fruit yield, and distinguish between marketable and unmarketable fruits to assess economic performance (Yismaw et al., 2024). Additional yield-related variables such as fruit set, fruit retention, and yield per plant or per hectare are measured to characterize treatment effects on both productivity and fruit-size distribution (Bora et al., 2024). When treatments involve fruit thinning or fruit load per stem, measurements of fruit weight and number at different node positions or fruit counts per plant help quantify how source-sink manipulation alters final fruit mass and commercial yield.

Quality-related indicators, especially soluble solids content (Brix), are commonly assessed to link fruit weight responses with eating quality. Studies generally sample representative fruits from each plot, measure Brix with a refractometer, and record traits such as rind firmness, pulp firmness, juice content, and sugar fractions (reducing, non-reducing, and total sugars). Some trials analyze Brix alongside fruit length, diameter, and average weight to identify trade-offs between density or fruit load and sweetness, while others focus on cultivar × mulch or growth 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 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).

6.2 Verification of the applicability of watermelon fruit weight models across different ecological environments

Beyond goodness-of-fit within a single dataset, watermelon weight models must be evaluated for applicability across environments, especially when environmental factors are explicit inputs. Work on the adaptive potential of large watermelon collections illustrates that genotypes differ strongly in environmental plasticity for average marketable fruit weight, quantified using regression coefficients of genotype response (bi) and stability parameters such as Sgi and general adaptive capacity across multiple years and sites. These parameters effectively characterize how robust fruit weight performance is to fluctuating conditions, providing a conceptual analogue for assessing the environmental robustness of predictive models that incorporate fruit weight as an output trait (Serhiienko et al., 2023).

Model applicability across environments can also be approached through genotype×environment or drought-environment interaction analyses using multivariate tools. In muskmelon, AMMI and GGE biplot models were applied to fruit weight data across irrigation regimes, treating each drought level as an environment and identifying genotypes with stable fruit weight under mild to severe soil water depletion. The GGE biplot classified irrigation regimes into a single mega-environment and distinguished genotypes with wide adaptability and stability, demonstrating that statistical modeling of performance across contrasting water regimes can objectively test whether a predictive framework (or genotype response surface) remains valid under varying ecological conditions (Rad and Bakhshi, 2020).

6.3 Sensitivity and stability analysis of watermelon fruit weight models

Sensitivity and stability analyses clarify how strongly fruit weight predictions depend on specific inputs or environmental drivers, and whether the model behaves reliably under stress or management changes. In a simplex lattice design modeling watermelon fruit weight as a function of poultry, cow, and goat manures, second-order mixture models were fitted and evaluated using analysis of variance; significant F-values and low p-values indicated that the quadratic models were adequate for prediction and captured the effects and interactions of nutrient components on fruit weight. Examining the estimated coefficients and interaction terms provided practical insight into which manure sources most strongly influenced model outputs and under what combinations the model predicted maximum fruit weight per plant.

Stability in the face of environmental variability is also addressed indirectly in studies that quantify genotype stability and plasticity for average fruit weight across multi-year, multi-environment trials. Using parameters such as genotype stability (Sgi), specific adaptive capacity, and plasticity coefficient (bi), large watermelon collections were partitioned into intensive, medium, and highly plastic groups with respect to total and marketable yield and average fruit weight, effectively ranking genotypes by how consistently they express fruit weight under changing conditions. While these analyses focus on biological responses rather than explicit prediction models, the same stability statistics and multi-environment frameworks can be incorporated into model validation protocols to test whether watermelon fruit weight prediction models maintain performance across diverse ecological and management scenarios (Serhiienko et al., 2023).

7 Case Study: Application of Watermelon Fruit Weight Prediction Based on Multiple Environmental Conditions

7.1 Data sources from typical watermelon cultivation regions

Case studies on watermelon fruit weight modeling can draw on diverse cultivation systems, from rain-shelter or greenhouse production to fully open-field systems. Under rain-shelter structures, fertigation trials with water-soluble NPK generated detailed records of leaf traits, fruit weight and quality, enabling regression analyses that identified 125% of the conventional NPK rate as optimal for fruit weight in protected conditions (Figure 3) (Hafiz et al., 2024). In contrast, open-field experiments with soil-moisture-sensor-based drip irrigation under different mulches in North Dakota produced multi-year datasets combining average fruit weight, diameter, and quality traits with rainfall and irrigation records, providing a basis for environment-response modeling in a cool, continental climate (Vaddevolu et al., 2021).

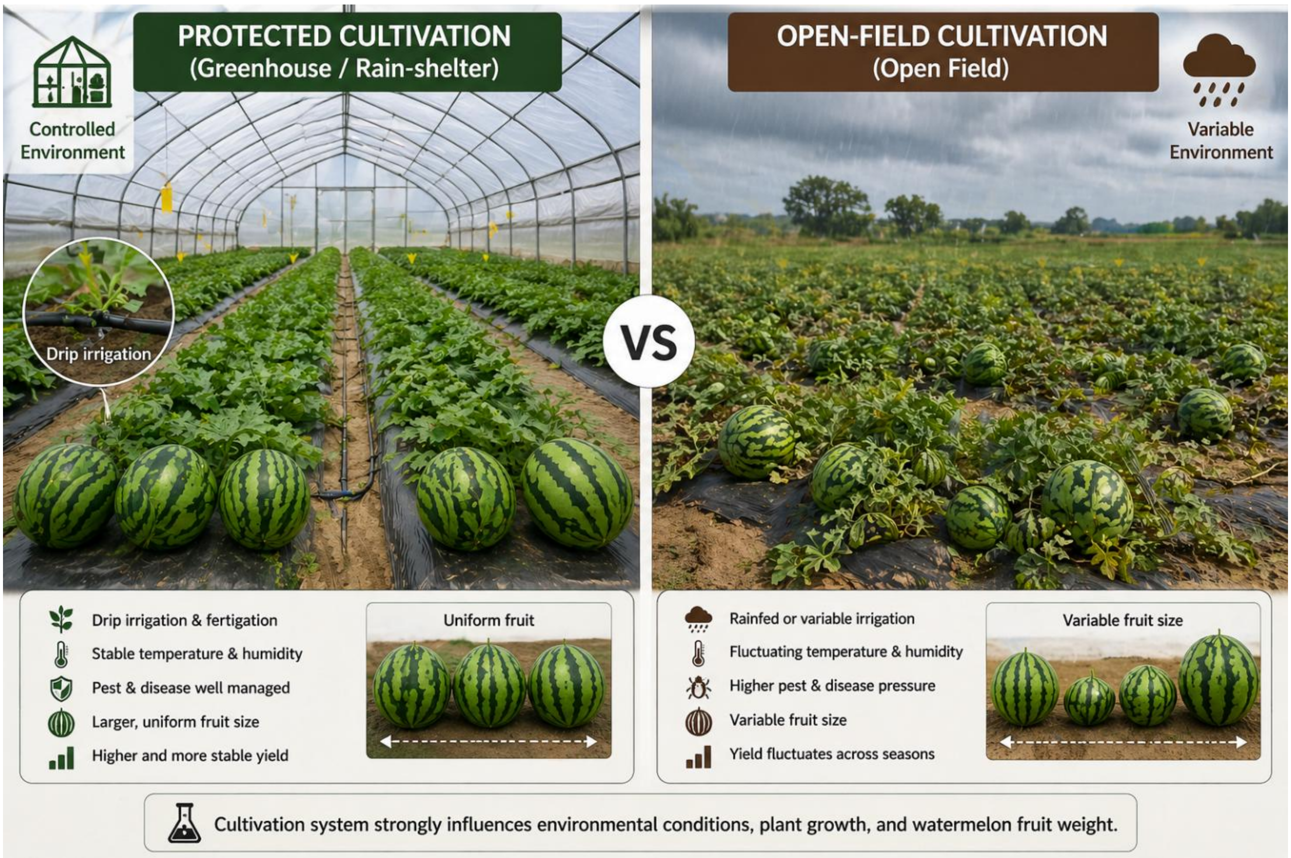

Figure 3 Comparison of protected cultivation and open-field systems used as data sources for watermelon fruit weight modeling under contrasting environmental conditions

Additional environmental contrasts arise from agroforestry versus sole-cropping and from seasonal variation in tropical open fields. In a semi-arid Chinese apple-watermelon agroforestry system, three irrigation quotas were combined with two planting patterns, generating three-year time series for soil water content, photosynthesis, fruit weight, and total yield under systematically different light and water regimes (Qiang et al., 2024). In tropical Tanzania, cultivar trials across dry and wet seasons recorded vine growth and fruit weight under markedly different rainfall and temperature conditions, showing that environmental seasonality significantly modifies yield traits and thus should be reflected in regional fruit weight prediction datasets.

7.2 Analysis of prediction results from watermelon fruit weight models under different environmental scenarios

Non-destructive, image-based models illustrate how fruit weight can be predicted across environments where direct weighing is impractical. A U-Net segmentation plus machine-learning pipeline used simple geometric ratios from fruit images to predict watermelon weight, achieving best training performance with Random Forest and Decision Tree models ($R^2 \approx 0.91$), and highlighting that larger variation in fruit size and image occupation can reduce accuracy relative to other fruits (Koç and Kayra, 2024). An IoT system integrating soil moisture, temperature, humidity, light, and CNN-based image analysis in melon-watermelon cultivation further reported very high sensor reliability and fruit weight prediction accuracies from 99.25% to 99.93%, demonstrating the potential of combining environmental sensing and imaging for real-time prediction under variable field conditions (Sarosa et al., 2024).

Where explicit process-based crop models are used, environmental scenarios such as deficit irrigation and mulching regimes can be evaluated through calibrated simulations. In Ethiopia, an AquaCrop application used soil physical data, climate, and crop records from factorial combinations of water application (50% vs. 100% soil-moisture depletion levels), mulching, and four watermelon varieties to predict yield responses; model performance for mulching-deficit irrigation effects on productivity was acceptable, with RMSE 0.70, Nash-Sutcliffe efficiency 0.65 and R 0.80. These simulations captured changes in fruit size (diameter, length, and average fruit weight) and yield under water-saving practices, supporting their use as scenario tools for fruit weight formation under constrained irrigation (Gebeyhu and Markos, 2023).

7.3 Model-based optimization of watermelon cultivation management (irrigation, fertilization, and temperature control)

Model outputs linked to irrigation strategies allow optimization of water allocation while maintaining fruit weight. In Mediterranean open fields, staged deficit-irrigation experiments quantified how applying 75%-50% of crop water requirement at vegetative, fruit development, or ripening stages reduces average fruit weight, fruit number, and marketable yield, with ripening identified as the least sensitive stage to water shortage. Similarly, Heliyon-based AquaCrop simulations for Ethiopian mulched systems showed that straw mulching plus 50% deficit irrigation with suitable varieties (e.g., Green Pearl) maximized land and water productivity while maintaining competitive average fruit weights, guiding irrigation scheduling and variety choice under scarcity (Gebeyhu and Markos, 2023).

Fertilization and coupled water-nutrient management can also be optimized using regression and structural approaches informed by model results in related cucurbits. Under rain-shelter watermelon, regression trendlines indicated that a 25% increase above standard NPK (125%) maximized fruit weight and vegetative growth under fertigation, suggesting that fertigation-based models should include fertilizer rate as a continuous decision variable in protected systems (Hafiz et al., 2024). For melon, structural equation modeling under varied water and fertilizer levels identified photosynthetic rate and total dry mass as key intermediates by which water and nutrient inputs control yield and quality, implying that watermelon fruit weight optimization models should similarly treat growth and photosynthesis as mediating variables when evaluating combined irrigation-fertilization strategies across arid and semi-arid environments (Yang et al., 2023).

8 Discussion and Outlook

Most existing watermelon fruit weight models are empirical and developed under narrowly defined conditions, limiting their transferability to other farms and seasons. For example, a tillage-based yield model was fitted using soil physical properties and simple plant traits, achieving very high R^2 (0.98) but relying on linear and weakly nonlinear relationships derived from only two seasons in a semi-arid Nigerian environment. Similarly, mixture models relating poultry, cow, and goat manure rates to fruit weight produced statistically significant quadratic equations, yet they describe only manure effects and do not explicitly account for weather, irrigation scheduling, or pest pressure that commonly constrain yield in practice. Non-destructive image-based models reach high fitting accuracy but also reveal important limitations. A U-Net plus machine-learning approach predicted watermelon weight from image features with $R^2 \approx 0.91$, but training relied on controlled image acquisition at fixed distances and backgrounds, conditions that are rarely met in commercial fields or heterogeneous greenhouses. Furthermore, the authors noted that prediction success is influenced by the diversity and complexity of products in the images, implying that substantial recalibration or retraining would be required when moving from experimental datasets to large-scale, multi-variety production systems.

Watermelon fruit weight responds to interacting environmental drivers rather than isolated factors, which complicates modeling. A three-way factorial experiment in northern Tanzania showed that extra irrigation or fertilizer alone did not increase fruit weight, while pollination strongly affected the probability of setting a second marketable fruit and improved sugar content, with complex higher-order interactions among water, fertilizer, and pollination on fruit initiation. Supplemental hand-pollination across 13 farms increased average fruit weight by 1.3 kg while responses to soil moisture varied with treatment, demonstrating that both biotic (pollinators) and abiotic (soil carbon and water) factors jointly regulate fruit set, abortion, and final weight. Greenhouse experiments further highlight strong water-nitrogen-CO_2 interactions on growth and yield. Under elevated CO_2, increased irrigation improved dry matter accumulation, photosynthesis, and yield, while higher CO_2 partly compensated for low nitrogen, shifting optimal N rates relative to ambient CO_2 scenarios (Hong et al., 2022). The interaction of irrigation and nitrogen significantly affected key physiological indicators such as net photosynthetic rate and transpiration, and integrated evaluation (TOPSIS) showed that comprehensive growth was positively correlated with yield, implying that fruit weight models must incorporate coupled water-nutrient-CO_2 effects rather than treating each driver independently.

Intelligent irrigation-fertigation systems and IoT platforms offer promising tools to regulate environmental drivers in real time and indirectly stabilize fruit weight. In greenhouse watermelon, an intelligent drip-fertigation system used soil-moisture sensors and IoT-based controllers to adjust irrigation limits and nutrient supply by growth stage, reducing water, N, P_2O_5 and K_2O inputs by 33%-72% without compromising yield or fruit quality. Dry matter accumulation and nutrient uptake followed logistic curves, and improving root traits under intelligent fertigation enhanced water and nutrient acquisition, suggesting that such systems could be coupled with fruit weight models to optimize source-sink balance during the fruit expansion phase. More integrated smart-farming architectures are also emerging for melon and watermelon. An IoT system combining soil moisture, temperature, humidity, and light sensors with CNN-based image analysis automatically regulated watering while predicting fruit weight with accuracies above 99%, and achieved very high reliability of nutrient, pH, and moisture sensors. Broader reviews of AI-IoT in precision agriculture emphasize that fusing remote sensing, high-throughput phenotyping, and machine-learning analytics enables site-specific irrigation and fertilization, automated crop monitoring, and yield forecasting, but also note challenges in data integration, scalability, and real-time decision support that must be addressed before such systems can be widely deployed for watermelon fruit weight regulation.

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Conflict of Interest Disclosure

The author affirms that this research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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