Computational Molecular Biology 2026, Vol.16, No.2, 129-145
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Review Article Open Access

Modeling the Relationship between Temperature and Tomato Yield in Greenhouse Systems

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Computational Molecular Biology, 2026, Vol.16, No.2 doi: 10.5376/cmb.2026.16.0010
Received: 22 Feb., 2026
Accepted: 30 Mar., 2026
Published:15 Apr., 2026

Preferred citation for this article:
Feng X.Z., 2026, Modeling the relationship between temperature and tomato yield in greenhouse systems, Computational Molecular Biology, 16(2): 129-145 (doi: 10.5376/cmb.2026.16.0010)

Abstract Temperature is one of the most critical environmental factors affecting the growth, development, and productivity of greenhouse tomatoes. This paper systematically reviews and analyzes the relationship between temperature dynamics and tomato yield formation under protected cultivation conditions. The study summarizes the physiological mechanisms through which temperature regulates photosynthesis, respiration, flowering, fruit set, and stress responses during different growth stages. In addition, the characteristics of greenhouse microclimates and the interactions between temperature, humidity, light, and CO_2 are discussed. Various modeling approaches, including statistical regression models, process-based crop models, and machine learning algorithms, are evaluated for their ability to predict tomato yield under variable temperature conditions. The paper also examines methods for model calibration, validation, and performance assessment using multi-season datasets. Several case studies are presented to demonstrate the practical applications of temperature-yield models in greenhouse management and precision agriculture. Finally, the challenges, limitations, and future prospects of intelligent temperature regulation and climate-adaptive modeling are highlighted to support sustainable greenhouse tomato production.

Keywords Greenhouse tomato; Temperature dynamics; Yield prediction; Crop growth model; Precision agriculture

1 Introduction

Greenhouse tomato production has become essential for ensuring stable, year-round supply while making efficient use of land, water, and energy. Within these protected systems, temperature is a primary driver of plant development, resource use, and ultimately yield, and its role is intensifying under climate change and more frequent heat extremes (Kürklü et al., 2025). Elevated temperatures and longer hot seasons already reduce yield, force higher cooling and irrigation demands, and complicate climate control in commercial greenhouses. At the same time, the greenhouse structure creates opportunities to actively manage temperature and to exploit its buffering capacity, provided that quantitative relationships between temperature regimes and tomato yield are well understood (Flores-Velázquez et al., 2022). Developing models that link temperature dynamics to yield is therefore important for climate-resilient design, control, and strategic planning in greenhouse tomato systems.

Over the past decades, numerous experimental and monitoring studies have examined tomato responses to greenhouse temperature. Work in high-tech and plastic houses shows that small but persistent temperature differences within a single compartment (on the order of 3 °C in daily averages) can significantly alter stem growth, fruit growth, and truss mass, even when bulk climate appears uniform (Šalagovič et al., 2024. Experiments manipulating air or soil temperature demonstrate substantial effects on photosynthesis, dry-matter accumulation, quality traits, and yield, with warmer root zones or air generally increasing yield and water productivity up to an optimum, beyond which heat stress causes losses (Efeta et al., 2025). Heat-stress trials further reveal strong genotype-dependent yield declines and quality changes, underscoring the importance of temperature thresholds and exposure duration around flowering and fruit set. Recent climate-change-oriented studies highlight that extreme high temperatures in commercial greenhouses already cause substantial yield losses (often >10%) and sharply increase resource use, confirming temperature as a critical vulnerability factor in modern soilless systems.

On the modeling side, several frameworks explicitly integrate temperature into greenhouse tomato yield prediction. Dynamic crop models such as TOMGRO represent organ initiation and growth via temperature-responsive source-sink processes, calibrated under controlled temperature, CO_2 and light conditions, and have been proposed as tools for environment control decisions (Higashide, 2022). Yield models developed for model-based greenhouse design implement literature-based temperature effects on yield and reproduce responses under both near-optimal and sub-optimal regimes, including extreme diurnal oscillations in contrasting climates. Spatially explicit approaches combining geostatistics with crop growth models show that ignoring intra-greenhouse temperature heterogeneity can bias simulated development rates and yield, particularly between central zones and sidewalls. More recently, integrated climate-and-yield models for specific greenhouse types, such as Chinese solar greenhouses, have been validated against multi-site experiments and used to explore design and operational scenarios, again emphasizing indoor air temperature as a key determinant of predicted yield (Zhou et al., 2025).

Against this background, the present study focuses on modeling the relationship between temperature and tomato yield in greenhouse systems. The first objective is to quantify how different descriptors of temperature regimes-such as daily mean, diurnal amplitude, spatial gradients, and the frequency and duration of supra-optimal events-affect yield and its components under realistic microclimate variability. The second objective is to incorporate these relationships into a modeling framework suitable for coupling with greenhouse climate models and control strategies, building on existing dynamic and design-oriented yield models while simplifying where necessary for operational use. The central hypotheses are that: (i) tomato yield in greenhouses is a non-linear function of both average temperature and exposure to critical heat or cold thresholds at sensitive stages; (ii) explicit representation of intra-greenhouse temperature variation improves yield prediction compared with models using only bulk climate; and (iii) a temperature-focused yield model can support evaluation of design options and climate-control strategies under current and future climate conditions.

2 Physiological Basis of Temperature Effects on Tomato Growth and Yield

2.1 Temperature regulation of photosynthesis and respiration

Tomato photosynthesis operates optimally within a moderate temperature range; deviations in either direction impair carbon gain and growth. Greenhouse and field studies show that high air temperatures, especially above about 38-40 °C, reduce net photosynthetic rate, stomatal conductance and ultimately fruit yield, reflecting damage to both CO_2 assimilation and water relations over time (Figure 1) (Liu et al., 2023). Sub-high temperature combined with high light (35 °C, 1000 $\mu mol \cdot m^{-2} \cdot s^{-1}$) sharply decreased net photosynthetic rate, Rubisco activity, PSII and PSI quantum yields, while increasing non-regulated energy dissipation and ROS accumulation, indicating irreversible photoinhibition of both photosystems when thermal and light loads coincide (Talukder et al., 2025).

Lower temperatures also limit photosynthesis by depressing chlorophyll content, electron transport and chlorophyll fluorescence parameters, resulting in reduced dry matter accumulation and yield (Zhang et al., 2023). Under sub-optimal day/night regimes around 15/10 °C, sensitive cultivars show greater reductions in fresh weight, chlorophyll content, Fv/Fm and electron transport rate than tolerant ones, whereas tolerant genotypes maintain higher soluble sugars and proline, supporting photochemistry and osmotic balance. Soil temperature interacts with shoot processes: moderate soil warming to about 26 °C increased leaf assimilation rate, chlorophyll, dry matter and yield in greenhouses, while also stimulating soil respiration and microbial biomass, suggesting coordinated temperature effects on root function and canopy photosynthesis.

Respiration is likewise temperature sensitive, affecting carbon use efficiency and growth. Analyses of tomato under high temperature indicate that respiration rates and growth rates shift together, with elevated temperatures increasing metabolic rates but also reducing metabolic efficiency and substrate carbon use (Alsamir et al., 2020). Nighttime respiratory costs interact with daytime photosynthesis to determine net biomass gain, and high night temperatures have been highlighted as critical constraints in warm greenhouse climates (Sato et al., 2006). Evaluations in solar greenhouses show that water-use efficiency at the leaf level is highest at 20-30 °C, beyond which heat shock reduces photosynthesis more than transpiration, lowering carbon gain per unit water and contributing to yield losses under hot conditions.

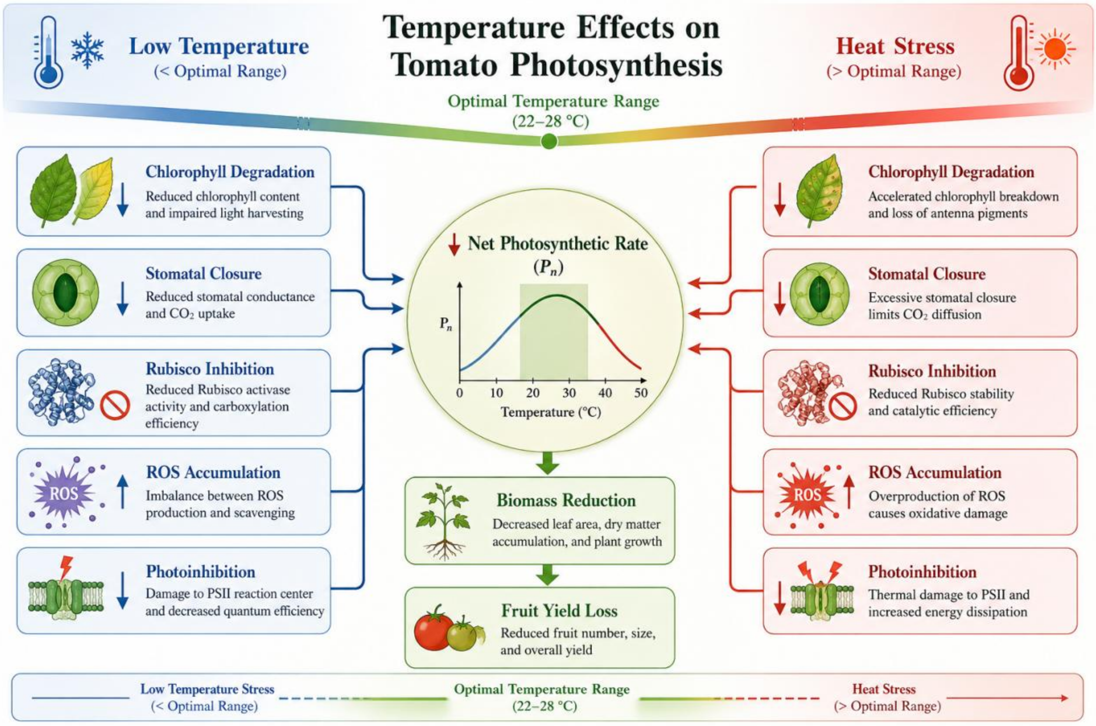

Figure 1 Conceptual diagram illustrating the effects of low and high temperature stress on tomato photosynthesis, photochemical efficiency, and yield formation

2.2 Effects of day/night temperature on flowering and fruit set

Tomato reproductive development is particularly sensitive to relatively small increases in mean day/night temperature. When day/night temperatures rose moderately from 28/22 °C to 32/26 °C, vegetative growth and photosynthesis remained largely unchanged, but fruit set, pollen viability and pollen release declined markedly, demonstrating that reproductive processes fail before canopy carbon assimilation under moderate heat (Sato et al., 2006). In controlled phytotron experiments across 20/24 to 27/37 °C night/day regimes, flowering and fruiting were normal at cooler treatments, but fruit set dropped sharply at 24/32 °C and nearly disappeared at 27/37 °C in most genotypes, underscoring the narrow thermal window for successful fertilization (Yadav et al., 2014).

Night temperature emerges as a key determinant of reproductive success. Work separating day and night effects shows that high night temperature (≥26 °C) at flowering is more detrimental to fruit set than a similar increase in day temperature, even when day temperature is already high. Earlier controlled-environment studies with 26 °C days and 18-26 °C nights reported that total and normal pollen production, seed content, and flower and fruit numbers on the first cluster were all higher at 18-22 °C nights than at 24-26 °C, although pollen germination in vitro could be favored at warmer nights, highlighting a complex trade-off between pollen formation and performance. Under fluctuating ambient day/night conditions in hydroponic summer production, early and late summer regimes with lower mean temperatures produced more flower clusters, fruits and higher yields than mid-summer regimes with warmer nights, again indicating that modest nocturnal warming can substantially depress reproductive efficiency and yield.

2.3 Heat and low-temperature stress mechanisms in greenhouse tomatoes

High temperatures in greenhouses trigger a cascade of morphological, physiological and reproductive disturbances that reduce yield and fruit quality. Reviews of tomato heat stress describe substantial flower abortion, up to about 80 % loss under severe episodes, along with impaired pollen viability and root growth, which together reduce fruit set and marketable yield (Alsamir et al., 2020). Experimental comparisons of high-temperature and control greenhouses show decreased stem diameter, plant height and fresh weight, elevated electrolyte leakage, lower relative water content, reduced photosynthetic efficiency and increased malondialdehyde, together with accumulation of phenolics, flavonoids and lycopene, consistent with membrane damage and activation of antioxidant defenses under chronic heat (Sellami and Kooli, 2026).

At the reproductive level, moderate but sustained temperature elevation during a critical pre-anthesis window disrupts specific metabolic processes in the androecium. Under 32 °C/26 °C, androecial glucose and fructose decline while sucrose increases, coinciding with reduced acid invertase transcript abundance, altered sugar metabolism and sharply reduced fruit set despite unchanged pollen production. Proline transporter expression on the microspore surface also falls under these conditions, suggesting impaired osmoprotection and turgor regulation in developing pollen. Conversely, screening of contrasting genotypes under high temperature in greenhouses reveals that tolerant cultivars can maintain fruit weight or even improve fruit hardness, whereas susceptible ones show large decreases in fruit size components, highlighting genotypic differences in maintaining reproductive function and fruit quality under heat (Rajametov et al., 2021).

Low temperature stress in greenhouse tomatoes also induces multi-level responses affecting both vegetative and reproductive stages. Reviews of cold responses report delayed flowering, enhanced pollen sterility and strong reductions in fruit set and yield, alongside decreased photosynthetic capacity due to impaired gas exchange, pigment content and chloroplast function (Yadav et al., 2021). Detailed analyses of sub-optimal day/night temperatures show that sensitive cultivars display greater declines in Fv/Fm, photochemical quenching and biomass than tolerant ones, while tolerant genotypes maintain higher levels of osmolytes such as soluble sugars and proline that support ROS scavenging and membrane stability. At the root level, exposure to low root-zone temperature (around 10 °C) reduces root activity, water and nutrient supply to shoots, lowers photosynthesis and chlorophyll fluorescence, and triggers accumulation of hydrogen peroxide, malondialdehyde and proline; only partial recovery occurs after re-warming, indicating lasting damage to the photosynthetic apparatus and growth potential (Zhang et al., 2023). Collectively, these mechanisms explain why both heat and cold episodes in greenhouses can depress tomato yield and underscore the importance of modelling temperature effects across this full stress spectrum.

3 Greenhouse Environmental Characteristics and Temperature Dynamics

3.1 Temperature distribution and microclimate formation in facilities

Air temperature in greenhouses is far from uniform, even when a single central sensor suggests a stable “bulk” climate. Multi-year monitoring in commercial tomato greenhouses has revealed horizontal gradients of up to about 3 °C in daily average temperature and 0.6 kPa in vapour pressure deficit (VPD), driven by structure, airflow patterns, and crop canopy (Šalagovič et al., 2024). These small but persistent differences translated into measurable variability in stem growth, fruit growth rate, and truss mass between locations, indicating that microclimate heterogeneity can meaningfully affect yield. Similar work in single- and multi-span houses reported horizontal temperature differences on the order of 1 °C between center and sides, confirming that assumptions of homogeneous air conditions are unrealistic for modern structures and should be revisited in energy and climate calculations (Ogunlowo et al., 2021).

Vertical stratification further complicates the thermal environment, particularly in tall or large-span facilities. A combined experimental-numerical study in a plastic greenhouse found that air near the roof could be more than 13 °C warmer than air lower in the crop zone at midday, with much smaller differences in the morning (Li et al., 2024). Computational fluid dynamics simulations that explicitly account for crop transpiration and optical effects show that plant canopies can increase temperature standard deviation by more than 30% compared with bare-structure assumptions, and that the hottest air often resides just below the roof where solar gains concentrate (Xu et al., 2022). Field studies in low-automation Mediterranean tomato houses report horizontal differences up to 7 °C-10 °C at certain times, highlighting how limited ventilation and solar load interact to create spatially complex microclimates that challenge single-point monitoring strategies.

3.2 Interaction between temperature, humidity, CO_2, and radiation

Temperature in greenhouses co-varies tightly with relative humidity and VPD, shaping plant responses more than any single variable alone. Microclimate monitoring in commercial tomato systems showed that zones with slightly higher temperatures tended also to exhibit higher VPD, and these combined conditions influenced local growth and fruit development more strongly than either driver considered independently. A detailed sensor-network study using an IoT-based "optimality degree" index quantified how diurnal swings in temperature of nearly 15 °C between day and night were accompanied by large changes in RH and VPD, often driving the climate outside tomato comfort ranges for substantial portions of the day (Rezvani et al., 2020). In warm seasons, natural ventilation alone was insufficient to prevent thermal inversion, leading to high humidity and sub-optimal VPD at night even as daytime conditions became too hot and dry, underscoring the need to manage temperature and humidity jointly rather than in isolation.

Radiation and CO_2 further modulate how temperature and humidity translate into crop performance. Reviews of greenhouse horticulture under climate change in the Mediterranean emphasize that rising temperature, declining RH, increasing VPD and modified solar radiation typically act together, often pushing microclimates beyond optimal thresholds for photosynthesis, transpiration, and reproductive development (Fanourakis et al., 2025). In such conditions, high radiation loads during heat events can exacerbate canopy temperature and water demand, while CO_2 enrichment or shading and cooling strategies may partially offset stress but also alter energy and water use. Process-based and data-driven crop models increasingly incorporate temperature, humidity (via stomatal conductance or VPD), CO_2 and shortwave radiation as coupled drivers, demonstrating that realistic prediction of biomass or yield requires capturing interactions among all four rather than simple temperature sums alone (Sun et al., 2025).

3.3 Seasonal and regional variations in greenhouse temperature regimes

Seasonal shifts in outside climate strongly reshape greenhouse temperature regimes and their suitability for tomato production. Long-term microclimate monitoring in tomato greenhouses has shown distinct spring-summer-autumn patterns, with larger intra-house gradients and more frequent exceedance of high-temperature thresholds during summer, even when the annual mean appears acceptable. An IoT-based assessment in Iran quantified "optimality degrees" for temperature, RH and VPD and found that winter months achieved higher overall optimality, largely because heating systems maintained conditions near target ranges, whereas in summer the lack of automated cooling produced long periods with daytime temperatures above 34 °C and night temperatures below 17 °C, unsuitable for tomato growth (Figure 2) (Rezvani et al., 2020). Numerical analyses of soilless glasshouses in North Africa similarly demonstrated strong seasonal effects on indoor profiles, with differences in roof-level temperatures between crop and no-crop scenarios narrowing but not eliminating the impact of external seasonal forcing (Abid et al., 2024).

Regional climate also determines baseline greenhouse temperature challenges and thus the design of appropriate control strategies. A systematic review across climatic zones reported that optimal tomato production in Mediterranean and arid regions typically requires carefully controlled ranges around 18-25 °C, with rising ambient temperatures reducing yields by more than half in some simulations when air temperatures approach 35 °C (Nițu et al., 2025). Survey-based evidence from high-tech soilless tomato greenhouses in Türkiye showed that extreme heat events during one season led to yield losses averaging 12.5%, alongside substantial increases in water, fogging, fertilizer and electricity use, and widespread reports of difficulty in climate control (Kürklü et al., 2025). In colder regions, solar or soft-shell greenhouses can increase average indoor temperatures by 10 °C-15 °C above outdoors during winter, greatly reducing low-temperature stress but at the cost of pronounced diurnal swings that must be managed to avoid humidity problems and localized stress hotspots. Across structures, seasons and regions, greenhouse temperature dynamics emerge from interacting structural, radiative and airflow processes, tightly coupled with humidity, CO_2 and radiation. Spatial heterogeneity and seasonal-regional contrasts are large enough to influence tomato growth and yield, indicating that both empirical analysis and modeling of temperature-yield relationships must explicitly represent microclimate patterns rather than rely on single-point or season-average conditions.

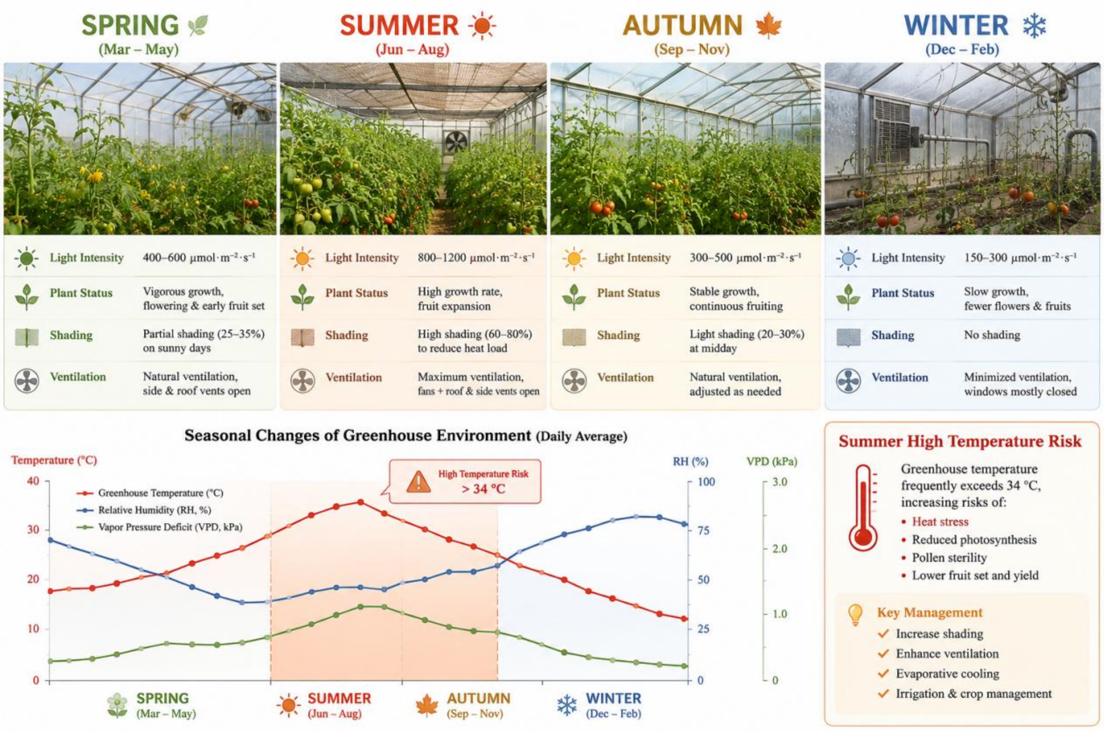

Figure 2 Seasonal variation in greenhouse tomato microclimate conditions, including temperature, relative humidity, and vapor pressure deficit across spring, summer, autumn, and winter periods

4 Tomato Yield Formation and Temperature Sensitivity

4.1 Yield components of greenhouse tomato

Tomato yield in greenhouse systems is determined by the interaction of fruit number, fruit size, and fruit dry matter content, all of which are sensitive to temperature. Yield components such as flower number, fruit set, and number of fruits per plant have been repeatedly proposed as primary markers of performance under heat, because they directly reflect reproductive success under stressful thermal regimes (Ghabileh et al., 2024). In many screening and physiological studies, genotypes that sustain higher fruit set and fruit number under high temperature also maintain higher overall yield, indicating that temperature sensitivity of these components largely controls production potential (Ro et al., 2021).

Fruit size and mass are additional key components shaping final yield. High temperature in greenhouses commonly reduces fruit weight, diameter, and firmness, with reported declines in susceptible cultivars of more than 30% in fruit weight compared with normal temperature conditions (Rajametov et al., 2021). Experimental increases of mean temperature by only a few degrees during fruit development have also been shown to reduce fruit size and alter sugar-acid balance, demonstrating that relatively small thermal shifts can reshape both quantitative and qualitative yield traits. At the same time, modeling and dry-matter studies in greenhouse tomato indicate that high yields are associated with improved total dry-matter production and efficient partitioning to fruits, suggesting that temperature effects on canopy photosynthesis and source-sink balance feed through to both fruit number and fruit size.

4.2 Critical temperature thresholds during different growth stages

Temperature thresholds governing tomato yield are strongly stage-dependent, with the reproductive phase showing the greatest sensitivity. Reviews of heat stress in tomato identify upper threshold temperatures around 30 °C-35 °C as critical for many processes, noting that temperatures above about 35 °C can inhibit seed germination, vegetative growth, flowering time and fruit set (Lee et al., 2022). In commercial protected cultivation in hot Mediterranean summers, mean daily temperatures of 25 °C-26 °C already appear to represent an upper limit for proper fruit set and yield, with even modest reductions of 1 °C-1.5 °C and higher humidity improving pollen viability and fruit set rates (Harel et al., 2014).

Flowering and early fruit set are especially vulnerable to exceedance of these thresholds. Controlled and field experiments consistently show that prolonged daytime or nighttime temperatures above about 32 °C/20 °C (day/night) during the reproductive phase reduce fruit set and fruit weight, leading to significant yield losses (Miller et al., 2021). Studies of pollen performance under episodes of 30 °C-34 °C or short heat shocks around anthesis report sharp declines in pollen viability, germination, and tube growth, which then translate into lower seed set and smaller fruit mass (Zepeda et al., 2026). Conversely, work on optimal ranges and growth-stage specific limits indicates that night temperatures above roughly 21 °C can already discriminate heat-tolerant from heat-sensitive cultivars, emphasizing that even moderate nocturnal warming beyond cultivar-specific thresholds during flowering can markedly depress yield formation.

4.3 Relationship between temperature accumulation and yield stability

Beyond instantaneous thresholds, tomato yield stability in greenhouses reflects the cumulative exposure to supra-optimal or sub-optimal temperatures over the season. Long-term heat stress experiments under greenhouse conditions show that yield loss increases with the duration of exposure: cherry tomato accessions subjected to elevated day set-points for more than 50 days exhibited progressive reductions in harvest index and fruit yield, with some genotypes losing over 40% of yield relative to controls (Park et al., 2023). Recent modeling work combining greenhouse climate projections with morphological yield models similarly demonstrates that future scenarios with 1-8 °C warming and longer hot seasons can decrease yield in heat-sensitive accessions while slightly increasing or stabilizing yield in more heat-resilient ones, highlighting the role of accumulated heat load in determining long-term yield trajectories (Kim et al., 2025).

Temperature accumulation interacts with developmental timing to shape yield stability. A mechanistic model of seed set and fruit mass that incorporates short periods of low (14 °C) and high (30 °C-34 °C) temperature shows that both the level and duration of deviation from the optimum critically affect pollen quality, seed set, and resulting fruit mass, with repeated or longer stress episodes causing cumulative reductions in fruit number and size on a truss (Zepeda et al., 2026). Multi-environment trials comparing performance under optimal field, high-temperature field, and high-temperature greenhouse conditions further confirm that yield stability differs strongly among genotypes: some maintain relatively constant fruit set and yield across environments, while others exhibit steep declines under repeated high-temperature episodes (Ro et al., 2021). Together, these findings support the use of temperature sums or heat-stress indices over sensitive stages as key predictors of yield stability in greenhouse tomato production.

5 Data Acquisition and Experimental Design

5.1 Experimental materials, greenhouse conditions, and cultivation management

Greenhouse tomato studies typically specify cultivar choice, planting density, and structural characteristics to ensure reproducibility and to contextualize yield responses. Experiments on cherry tomato ‘Cheramy F1’ in winter greenhouses used a randomized complete block design with split plots, three rows and three replications, with three plants sampled per row, capturing variability over two consecutive seasons (Arshad et al., 2024). Within this structure, the internal climate ranged from about 8-41 °C across vegetative and fruiting stages, with CO_2 between roughly 386-510 ppm and light intensity from about 95-240 W m^{-2}, providing a broad envelope of temperature regimes for modeling. Other greenhouse trials with large-fruited cultivars have similarly defined plot structure through factorial or split-split plot designs, for example combining cultivar, grafting and plant density (3.5 vs. 5.5 plants m^{-2}) in hydroponic organic systems to test management interactions under hot, humid conditions (Dash et al., 2023).

Representative experimental work also reports greenhouse size, location, and baseline climate. A Ghanaian study used a 270 m^2 greenhouse at a defined latitude, planting tomato ‘Anna F1’ in a 3×3 factorial of spacing and topping treatments, with temperature and relative humidity maintained between 24 °C-32 °C and 63%-80% during the experiment. Orientation and row spacing have been explicitly treated as design variables in Chinese solar greenhouses, where north-south versus east-west orientations and 1.4-1.8 m row spacings were compared to analyze effects on canopy light interception, growth, and yield (Li et al., 2024). Fertilization and soil or substrate management regimes are usually standardized within each trial; for example, integrated fertilization-tillage experiments in greenhouses applied defined NPK formulations and organic amendments across rotary tillage and plowing systems, and quantified biometric and yield traits under each treatment (Avasiloaiei et al., 2025). Together, such designs provide a template for specifying cultivars, structure, and management in temperature-yield modeling studies.

5.2 Temperature monitoring technologies and sensor deployment

Capturing temperature-yield relationships requires dense, reliable microclimate measurements rather than single-point records. Multi-year monitoring in commercial tomato greenhouses deployed multiple temperature-humidity sensors within the crop canopy, revealing spatial gradients up to about 3 °C in daily mean temperature and 0.6 kPa in vapour pressure deficit between locations, and linking these to local differences in stem and fruit growth (Šalagovič et al., 2024). Sensor networks are increasingly wireless: several studies describe custom wireless nodes or IoT platforms integrating temperature, relative humidity and sometimes CO_2 and light sensors, distributed at multiple horizontal positions and heights to resolve microclimate structure (Kolapkar and Sayyad, 2021). Such systems reduce cabling, facilitate relocation of nodes, and have been shown to detect microclimate layers between lower and upper canopy, as well as climate disturbances near walls or vents.

Recent work has combined distributed sensing with data fusion and model-based indices. In an Iranian commercial tomato greenhouse, a grid of 20 LoRaWAN wireless sensor nodes was installed on two horizontal planes at different heights, while an external weather station recorded outdoor conditions. Sensor calibration and validation were conducted offline in MATLAB/Simulink, and microclimate data were translated into an “optimality degree” index between 0 and 1 for temperature, RH and VPD, enabling direct assessment of how far local conditions deviated from crop comfort zones. Other wireless monitoring systems integrated fruit diameter sensors with 802.15.4-based temperature and radiation nodes and transmitted data via GPRS, achieving mean absolute temperature differences of only about 0.6 °C compared with wired systems, and data loss below 1%. Complementary approaches, such as compliant “plant wearables” measuring temperature and humidity directly on leaf surfaces, illustrate emerging options for ultra-localized microclimate characterization within greenhouse crops (Nassar et al., 2018).

5.3 Yield data collection and statistical preprocessing methods

Tomato yield data in greenhouse experiments are generally collected at plant or area level using standardized protocols, then subjected to statistical analysis and, in modeling studies, further preprocessing. Many agronomic trials quantify number of fruits per plant, individual fruit weight and total yield (e.g., $t \cdot ha^{-1}$ or $g \cdot plant^{-1}$) at one or more harvests, often alongside traits such as fruit size, firmness, soluble solids, and dry matter (Avasiloaiei et al., 2025; Ugbe et al., 2025). In cultivar or spacing-topping trials under greenhouse conditions, randomized or randomized complete block designs with three or more replications are analyzed using analysis of variance, with significance judged at $p < 0.05$ and treatment means separated by least significant difference or similar procedures. Microclimate-growth studies add growth rates of stems and fruits or truss mass at harvest, relating these to local temperature and VPD conditions over defined periods.

For data-driven modeling of temperature-yield relationships, more elaborate preprocessing is required. Yield-prediction studies using artificial neural networks and other machine-learning methods typically assemble datasets that combine environmental descriptors, management variables, and yield as inputs and outputs, then partition data into training and validation sets (Peng et al., 2023). A recent solar-greenhouse study compiled 390 datasets across multiple regions, each including planting density, organic and inorganic N, P, K rates, and effective accumulated temperature, with greenhouse tomato yield as the response; these variables were scaled and classified into different soil fertility levels before being used in neural-network models. In UAV-based yield prediction, ultra-high-resolution imagery was processed into hundreds of plant-level variables (e.g., means and higher-order statistics of vegetation indices), then reduced using feature-selection algorithms before model fitting (Tatsumi et al., 2021). Across these approaches, standard error metrics such as mean squared error, mean absolute error and coefficient of determination are calculated to evaluate predictive performance and to support sensitivity analysis of which environmental and management factors, including temperature descriptors, most strongly influence modeled greenhouse tomato yield.

6 Modeling Approaches for Temperature-Yield Relationships

6.1 Statistical regression models for yield prediction

Statistical regression remains a fundamental approach to quantifying relationships between temperature variables and tomato yield or its components in controlled environments. In greenhouse cherry tomato under prolonged heat stress, polynomial regression was used to relate external weather (solar radiation, maximum and minimum temperature) to in-house temperature and humidity, forming a climate sub-model that then fed a growth-yield model comparing heat-resilient and heat-sensitive accessions (Kim et al., 2025). This type of regression framework allows explicit estimation of how projected temperature increases of 1 °C-8 °C and longer hot seasons modify yield, and highlights contrasting harvest index responses between genotypes under future climate scenarios.

Regression has also been embedded in broader yield-prediction pipelines as a relatively transparent, data-efficient alternative to complex AI models. In industrial tomato, a platform evaluated multiple algorithms and ultimately selected Ridge regression to predict open-field yield from hybrid and in-season environmental data, achieving prediction errors acceptable to producers and demonstrating that linear penalized models can capture much of the climate-yield signal when sufficient multisite data are available (Kasimatis et al., 2025). Polynomial and multivariate linear regression have similarly been used to approximate nonlinear links between external climate and greenhouse temperature and humidity, with R^2 values above 0.8-0.9 for maximum and minimum temperature, providing statistically robust climate inputs for subsequent tomato yield modeling under both control and heat conditions.

6.2 Process-based crop growth models

Process-based crop models represent temperature effects mechanistically through development rates, photosynthesis, and dry-matter partitioning. The TOMGRO model, a dynamic, source-sink framework based on differential equations, simulates initiation, expansion and senescence of leaves, stems and fruits in response to greenhouse temperature, CO_2 and light; calibration in controlled environments showed that TOMGRO can accurately reproduce observed differences in growth and yield under contrasting temperature regimes, making it suitable for environment-control decisions. Extensions and related models such as TOMSIM and Vanthoor's greenhouse climate-yield model further decompose temperature impacts on processes including truss appearance rate, fruit growth period and dry-matter partitioning, and have been validated across locations with near-optimal and non-optimal temperature and radiation conditions (Figure 3) (Gong et al., 2021).

Cardinal-temperature-driven models refine these process representations by explicitly encoding temperature thresholds for phenology and yield formation. The CROPGRO-Tomato model was improved by updating species coefficients for cardinal temperatures governing pre- and post-anthesis development, leaf appearance, photosynthesis, fruit set and fruit growth, based on recent controlled-temperature experiments (Boote et al., 2012). Recalibration and evaluation against multi-site field data substantially reduced RMSE for leaf area index, fruit number, biomass and fruit dry weight, resulting in Willmott d indices above 0.92 and enabling more reliable prediction of tomato growth and yield responses to temperature change. More recently, an integrated greenhouse yield prediction model combined TOMGRO and Vanthoor structures, using sensitivity analysis and Bayesian optimization to adapt parameters to specific facilities; when tested against four years of greenhouse data, the integrated model produced much lower RMSE than either parent model, indicating that hybridization of process-based schemes can improve robustness under varying temperature regimes (Lin et al., 2019).

6.3 Machine learning and artificial intelligence approaches

Machine learning and AI approaches increasingly complement or replace traditional models for predicting tomato yield or temperature-driven intermediates. A systematic review of tomato-yield ML models found that about two-thirds of best-performing approaches were deep-learning based, with LSTM, generic artificial neural networks and support vector regression most frequently used when combining climate, soil, plant growth, fertilization and irrigation variables; random forest regression was particularly effective when using image-derived vegetation indices (Odah et al., 2025). In greenhouse applications, an ANN model trained on farm-level energy and input data outperformed multiple linear regression for predicting tomato yield, and sensitivity analysis identified key production factors, illustrating how neural networks can capture nonlinear interactions among management and environment beyond simple temperature terms (Belouz et al., 2022).

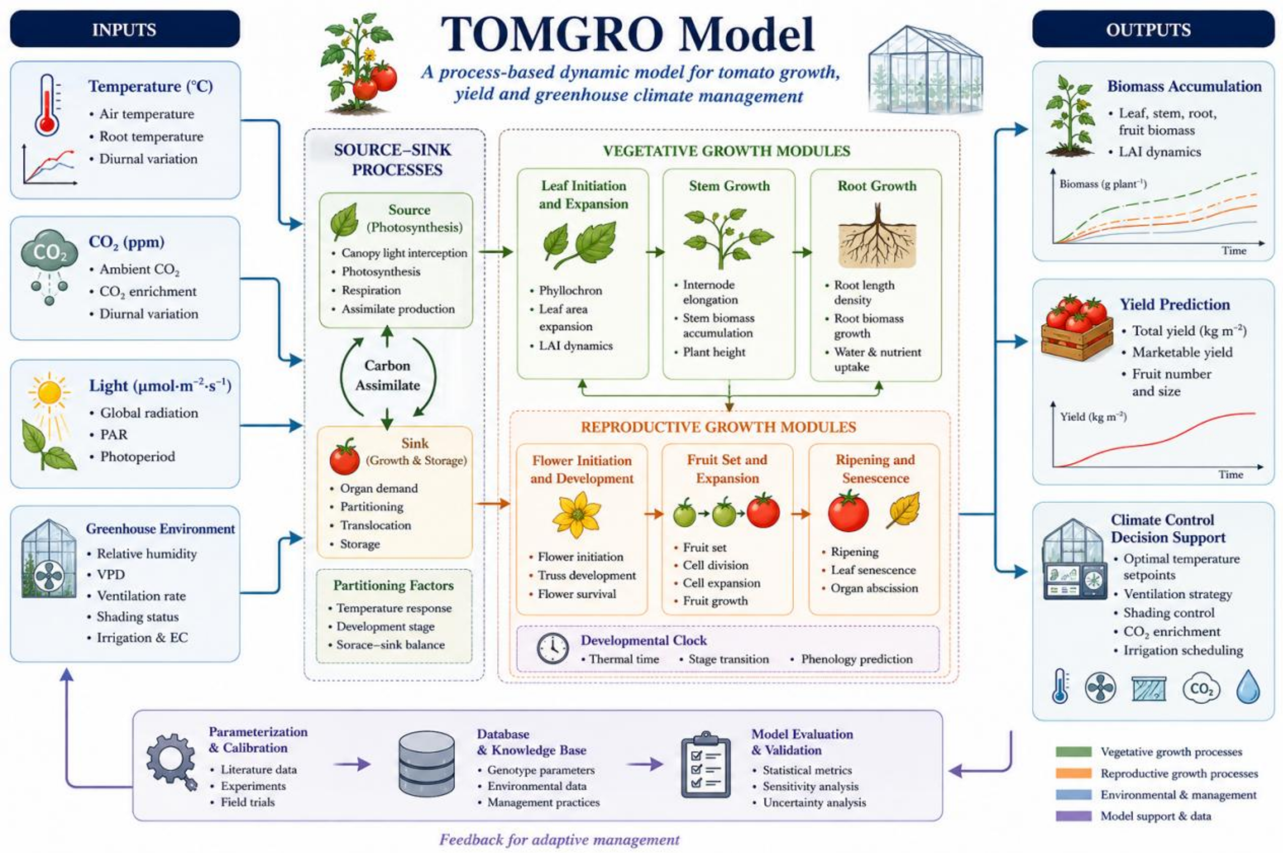

Figure 3 Framework of the TOMGRO process-based tomato growth model showing environmental inputs, source-sink interactions, and yield prediction outputs under greenhouse conditions

Recent studies focus more directly on greenhouse climate-yield linkages and short-term forecasting. A hybrid deep-learning framework combining temporal convolutional networks and recurrent neural networks was developed to predict tomato yield from time series of greenhouse microclimate variables (temperature, CO_2, humidity deficit, radiation) and historical yields, outperforming traditional ML and other deep architectures in RMSE across multiple commercial datasets (Gong et al., 2021). Another RNN-LSTM-based system predicted in-house temperature from external climate, then converted predicted temperatures to growing degree days and drove sigmoid growth models for leaf area index, fruit fresh weight and dry matter, achieving R^2 above 0.80 even when using forecasted rather than observed temperatures (Lin et al., 2024). Model-fusion strategies now integrate biophysical models such as reduced TOMGRO with CNN-RNN predictors, with neural-network fusion delivering higher yield-prediction accuracy than either component alone when applied to multi-year greenhouse temperature and CO_2 records.

7 Model Calibration, Validation, and Performance Evaluation

7.1 Parameter optimization and model calibration

Calibration of tomato temperature-yield models generally focuses on a limited set of influential physiological or empirical parameters, while less sensitive parameters are fixed from literature or prior studies. An integrated greenhouse tomato yield model combining TOMGRO and Vanthoor used an extended Fourier amplitude sensitivity test (EFAST) to classify parameters into optimized, fixed and ignored groups, thereby reducing dimensionality before calibration (Lin et al., 2019). The remaining parameters were then optimized with Bayesian optimization using multi-year greenhouse data, resulting in an RMSE of 2.60 for yield compared with values above 17 for the individual component models, indicating a much closer match between simulated and observed yields.

Dynamic process-based models follow similar workflows but employ different optimization tools. The DSSAT-CROPGRO-Tomato model calibrated its genetic and management parameters with the GLUE framework, achieving average relative errors around 3%-5% for phenology, plant height and yield dry weight under varying water and nitrogen supplies (Shan et al., 2025). For the HORTSYST model, global sensitivity analysis with Sobol's method first identified nine key parameters controlling photo-thermal time, dry matter production and transpiration; these were then calibrated with a differential evolution algorithm, yielding RMSE values close to zero for leaf area index, nitrogen uptake and dry matter in two greenhouse seasons (Martínez-Ruíz et al., 2021). In reduced TOMGRO, three evolutionary algorithms-genetic algorithm, particle swarm optimization and differential evolution-were compared for calibrating 14 key parameters using multi-year greenhouse datasets; performance was judged from RMSE, relative RMSE and MAE between measured and simulated mature fruit dry matter (Gong et al., 2021).

7.2 Validation using multi-season and multi-region datasets

Robust temperature-yield models must be validated beyond the calibration environment, using independent seasons and, when possible, contrasting regions. The integrated TOMGRO-Vanthoor yield model was verified against four years of greenhouse data, showing consistently high performance across variable environmental conditions, which supports its intended generality under changing greenhouse climates (Lin et al., 2019). AquaCrop was calibrated and validated for greenhouse tomato under full and deficit irrigation; the model reproduced fresh yield, biomass and water productivity for both treatments, and was then used with 30 years of historical weather data to simulate yield responses to external temperature changes, effectively extending validation across multiple climatic years (Locatelli et al., 2024).

Model-based greenhouse design work with the Vanthoor yield model explicitly demonstrated cross-region validity. After implementing temperature effects from a broad literature survey, the model was validated for four temperature regimes in the Netherlands and southern Spain, reproducing yields under both near-optimal and sub-optimal climates with varying light and CO_2. Data-driven yield prediction approaches also rely on multi-environment datasets: a neural-network model for solar greenhouse tomato was trained on 390 experiments from different Chinese regions and soil fertility levels, then evaluated separately within low, medium and high fertility classes to test its generalization across management and climatic gradients (Peng et al., 2023). For dynamic growth models such as HortSyst, autumn-winter and spring-summer greenhouse seasons were simulated, and good agreement for dry matter, nitrogen uptake and transpiration across both seasons indicated that calibrated parameters retained validity under distinct seasonal temperature regimes.

7.3 Evaluation indicators: RMSE, R^2, MAE, and model robustness

Quantitative evaluation of tomato temperature-yield models commonly relies on root mean square error (RMSE), mean (absolute) error, and coefficient of determination (R^2), often complemented by model efficiency or bias. In the integrated yield prediction model, RMSE for yield dropped from above 17 in TOMGRO and Vanthoor to 2.60 in the integrated version, reflecting a substantial improvement in predictive accuracy (Lin et al., 2019). HORTSYST calibration reported RMSE values for leaf area index, nitrogen uptake, dry matter and transpiration that were close to zero, together with high modeling efficiency, indicating that residuals were small relative to observed variability over two crop seasons. In greenhouse AquaCrop applications, RMSE and normalized RMSE were used to evaluate calibration and validation for fresh yield and biomass under full and deficit irrigation, with acceptable errors supporting subsequent use for long-term temperature impact assessment (Locatelli et al., 2024).

Machine-learning models for greenhouse processes and yield frequently add MAE and R^2 to characterize accuracy and robustness. A CatBoost-based model for tomato transpiration achieved $R^2 = 0.92$ over the whole growth stage, while its RMSE and MAE were reduced by more than 70% relative to a traditional crop-coefficient approach, and further partitioning by growth stage decreased RMSE by up to 97% at night during fruiting, illustrating gains in stability under different regimes (Tong et al., 2023). A neural-network yield model for solar greenhouse tomato across fertility levels reported that an improved particle-swarm-optimized network produced the smallest MSE and MAE and the largest R^2 (up to about 0.94), outperforming baseline networks under low, medium, and high fertility and thus demonstrating robustness across diverse environmental and management contexts (Peng et al., 2023). Broader crop-yield and evapotranspiration studies similarly adopt RMSE, MAE and R^2 as core indicators, emphasizing their usefulness for comparing alternative algorithms and for assessing generalization to unseen seasons or regions.

8 Case Studies of Greenhouse Tomato Temperature-Yield Modeling

8.1 Case study in solar greenhouses under winter cultivation

Winter tomato production in northern China has been used to demonstrate how temperature-yield relationships can be modeled in solar greenhouses. In soft-shell solar greenhouses, dynamic monitoring of light, temperature, and humidity for six cherry and three large-fruited cultivars was combined with yield and quality measurements to build correlation and partial least-squares path models linking microclimate to cluster yield and Brix (Liu et al., 2025). These analyses showed that soft-shell structures raised average daily temperature by 10 °C-15 °C and reduced low-temperature stress duration by 25%, with cherry tomato yield proving more temperature-sensitive than large-fruited types.

A complementary modeling approach integrated a mechanistic climate model with a tomato yield module specifically for Chinese solar greenhouses. This open-source model was calibrated and validated against three experiments, including two commercial winter production greenhouses, and achieved an RMSE of about 1.6 °C for indoor air temperature and 0.61-0.71 $kg \cdot m^{-2}$ for yield, while sensitivity analysis highlighted air-exchange parameters and optimal leaf area index as key determinants of simulated winter yield (Zhou et al., 2025). Active solar heating systems provide another winter case: in paired Canarian greenhouses, an active solar heating installation improved nocturnal thermal conditions and increased total tomato yield by 55% during the cold season, illustrating the strong leverage of improved temperature profiles on winter productivity (Bazgaou et al., 2021).

8.2 Case study in plastic tunnel systems under high-temperature stress

Plastic and walk-in tunnel systems in warm climates offer clear examples of modeling and managing high-temperature impacts on tomato yield. In southern China, daily maximum temperature and mean relative humidity inside plastic greenhouses were simulated using an extreme learning machine to identify high-temperature-high-humidity (HTHH) events, and response surfaces were then used to relate event frequency and return period to tomato physiological losses, showing that flower bud differentiation was the most temperature-sensitive stage (Zhang et al., 2022). The analysis revealed that HTHH events mainly occurred from June to September and that high temperature played a larger role than humidity in reducing growth indicators, providing a quantitative basis for risk assessment and regional layout of plastic-house tomato.

Experimental work in arid regions has focused on modifying tunnel microclimates and quantifying associated yield responses. In late-summer trials comparing a shaded net tunnel, a net tunnel with fogging, and a plastic tunnel with evaporative cooling, all powered by solar energy, cooled tunnels significantly improved leaf area, chlorophyll content, cell membrane stability, and relative water content, while reducing physiological disorders such as sunscald and blossom-end rot (Sharaf-Eldin et al., 2023). These microclimate changes translated into about 31.5% higher marketable yield with evaporative cooling and 28.8% with fogging relative to open field, demonstrating how engineered temperature reductions within plastic systems can be directly linked to yield gains.

8.3 Comparative case study of intelligent greenhouse temperature control strategies

Recent case studies in intelligent greenhouses explicitly couple temperature control strategies with crop and profit models. In the second “Autonomous Greenhouse Challenge”, five AI-supported teams remotely operated high-tech cherry tomato compartments for six months, using sensor data and algorithms to determine temperature, humidity, and CO_2 setpoints; all AI teams outperformed a reference human grower in net profit, with some teams applying higher early-season and end-season temperatures to accelerate development and ripening while still achieving better heat-use efficiency (Hemming et al., 2020). Analysis with a virtual greenhouse "digital twin" linked these distinct temperature trajectories to differences in yield and resource use, offering a comparative benchmark for data-driven climate strategies.

Model-based optimal control studies provide an additional perspective on intelligent temperature-yield management. A PSO-based model predictive control framework combined a greenhouse climate model with a biophysical yield model and optimized heating, ventilation, and lighting setpoints to maximize yield while minimizing energy costs, outperforming traditional control and genetic-algorithm-based MPC in both yield and energy efficiency in a tomato case study (Gong et al., 2023). At year-round scale, a rule-based MPC using external weather and month-averaged tomato prices to select temperature setpoints was compared with on/off control and open field; simulations for Beijing showed that only strategies jointly optimizing yield and energy cost achieved satisfactory profit, highlighting how economic and biophysical models must be integrated when evaluating intelligent temperature control options (Xu et al., 2024).

9 Discussion, Applications, and Future Perspectives

Existing temperature-yield models for greenhouse tomato are powerful decision-support tools but still face notable limitations and uncertainties. Process-based models often rely on a relatively small set of experiments for parameterization and may not fully capture the variability in low-technology or highly heterogeneous greenhouses, where temperature extremes and spatial microclimate variation are common. Global sensitivity and uncertainty analyses have shown that yield predictions can be highly sensitive to a few temperature-related parameters, such as thresholds for fruit abortion or growth inhibition, meaning that modest parameter errors can translate into large yield errors when conditions move outside the "ideal" range. Many models assume relatively uniform microclimate and well-controlled systems, so their validity can degrade in real commercial settings with imperfect heating and cooling, where optimality degrees for temperature and VPD fluctuate widely between seasons and locations. Furthermore, hybrid approaches that enhance process-based models with deep learning can boost accuracy, but they introduce their own sources of uncertainty related to training data representativeness, sensor noise, and potential overfitting, making model transfer to new greenhouses or future climates less certain unless explicitly tested.

Despite these limitations, temperature-yield models are increasingly embedded in precision agriculture and smart greenhouse platforms to support real-time management. Decision-support systems using crop water productivity models such as AquaCrop already leverage external temperature and long historical weather records to estimate greenhouse tomato yields and optimize irrigation under future climate scenarios. IoT-based microclimate monitoring frameworks quantify "optimality degrees" or comfort ratios for temperature, humidity and VPD, translating dense sensor data into simple indices that link directly to yield risk and guide heating and cooling strategies. Smart greenhouse platforms go further by combining wireless sensor networks, fuzzy or model-based controllers, and cloud dashboards, enabling automated ventilation, shading and irrigation tuned to maintain temperatures within crop-specific ranges. Integrated digital solutions that add machine learning yield predictors, disease recognition, and even fruit expansion analysis use historical temperature-humidity-yield relationships to recommend set-points and interventions, improving resource efficiency and stabilizing production. As these systems mature, temperature-yield models shift from purely research tools to operational components of climate control, irrigation scheduling, and energy optimization in commercial tomato production.

Future work on modeling temperature-yield relationships will likely be driven by convergence of digital twins, dense IoT sensing, and climate-adaptive algorithms. Greenhouse digital twins are beginning to integrate sensor networks, multivariate yield-forecasting models, and edge computing to provide continuous predictions of final yield based on evolving temperature and other climate variables, allowing growers to test "what-if" scenarios for alternative control strategies before applying them in the real house. Broader reviews of agricultural digital twins and smart farming envision virtual replicas that fuse crop models, weather forecasts, soil sensors, and aerial imagery, creating platforms where temperature-yield modules for tomato become part of a larger cyber-physical production system. Knowledge-based data-driven approaches that couple calibrated process-based models with deep learning show one promising route: process models preserve interpretability and physiological realism, while neural networks and particle filtering correct systematic errors and adapt to new microclimates or management regimes. At the same time, IoT reviews highlight persistent challenges around sensor accuracy, interoperability, and deployment cost, suggesting that future climate-adaptive modeling must explicitly handle data quality, uncertainty propagation, and robust control under extreme events. In this context, next-generation temperature-yield models will need to be both explainable and self-updating, closing the loop between sensing, prediction, and actuation to support resilient, low-carbon greenhouse tomato systems under a changing climate.

Acknowledgments

I would like to thank the anonymous reviewers for their detailed review of the draft. Their specific feedback helped us correct the logical loopholes in our arguments.

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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