

Article

Performance of AquaCrop and DSSAT Models for Greenhouse Grown Tomato Under High-Temperature Conditions

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Highlights

- AquaCrop achieves superior simulation performance under high-temperature conditions compared with the DSSAT model.
- Integrating XGBoost-derived ET_0 into AquaCrop enables multi-scenario simulation of greenhouse temperature and water regimes.
- Scenario simulations identified $1.1E_{pan}$ and $34\text{ }^{\circ}\text{C}$ for maximizing tomato yield.
- A strategy of $0.9E_{pan}$ and $32\text{ }^{\circ}\text{C}$ optimized tomato water use efficiency.

Abstract

High temperature is a primary meteorological hazard restricting crop yield and quality, particularly in semi-automatic greenhouses. However, the accuracy of crop models under controlled high-temperature conditions in greenhouses has rarely been examined. To address this, our study evaluated the AquaCrop (7.1) and DSSAT (4.8.2) models for greenhouse-grown tomato under high-temperature conditions. Field experiments were conducted over two consecutive years (2024 and 2025) with two temperature treatments (TH: daily maximum temperature $> 35\text{ }^{\circ}\text{C}$; TD: daily maximum temperature $< 35\text{ }^{\circ}\text{C}$) and two irrigation levels (WH: $100\%E_{pan}$; WD: $60\%E_{pan}$, where E_{pan} is cumulative pan evaporation). Key indicators were continuously measured, including canopy cover, soil water content, above-ground biomass, yield, and water consumption. Additionally, the XGBoost algorithm was introduced to estimate reference crop evapotranspiration across different treatment combinations, facilitating a multi-scenario analysis. The results indicated that under both TD and TH conditions, the AquaCrop model accurately simulated canopy cover ($RMSE \leq 6.84\%$, $NRMSE \leq 12.27\%$, $EF \geq 0.92$), yield ($PE \leq 12.20\%$), above-ground biomass ($PE \leq 2.34\%$), and water consumption ($PE \leq 10.33\%$) across different irrigation levels. However, its performance in simulating soil water content declined markedly under the TH treatment, with EF becoming negative in some cases ($-1.66 \leq EF \leq 0.43$), indicating that the model was largely ineffective for SWC under these conditions. The DSSAT model exhibited lower simulation accuracy under the TH treatment compared to the TD treatment, and its overall performance was slightly inferior to that of the AquaCrop model ($RMSE \leq 15.79\text{ mm}$, $NRMSE \leq 14.54\%$, $-1.68 \leq EF \leq 0.46$). Scenario analysis of 20 temperature and irrigation combinations, integrating XGBoost-derived ET_0 into the



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AquaCrop model, revealed that maximizing greenhouse tomato yield requires a combination strategy of $1.1E_{pan}$ and $34\text{ }^{\circ}\text{C}$, whereas optimizing water use efficiency is best achieved under $0.9E_{pan}$ and $32\text{ }^{\circ}\text{C}$. These findings provide a theoretical basis and technical support for the application of crop models and the development of environmental regulation strategies in greenhouse cultivation under high-temperature conditions.

Keywords: canopy cover; management strategy; soil water content; XGBoost algorithm; yield

1. Introduction

Greenhouses, as crucial structures for crop cultivation, are recognized globally, providing an ideal environment for crop growth, facilitating optimal growth and yield, and ultimately maximizing profits for growers [1]. The semi-automatic greenhouses serve as simple agricultural structures equipped with neither active heating nor cooling facilities. They are dominated by natural ventilation and demonstrate cost-effectiveness and efficiency in achieving high yields, ensuring year-round production of temperature-sensitive fruits and vegetables by fully harnessing solar energy, especially in northern China and broadly similar agricultural zones [2–5]. However, faced with water shortages and frequent extreme weather events, these greenhouse industries must improve production while reducing irrigation and environmental management inputs [6].

Temperature and water availability are the primary determinants of yield and quality in greenhouse crops. A scientific and rational temperature management strategy could provide a suitable environment for crop growth, especially in naturally ventilated greenhouses. However, such greenhouse facilities are highly susceptible to frequent heat stress episodes during the seasonal transitions from spring to summer and summer to autumn, severely compromising fruit yield and quality. Previously, temperature management in plastic greenhouses still relied on growers' experience, failing to fully exploit their production potential [7]. Unreasonable temperature management strategies often imposed severe environmental stress on crops, such as high temperature, high humidity, and their coupled effects, thereby affecting the normal growth of greenhouse crops. For instance, high temperature brought additional risks and production costs, while high humidity might lead to pest infestations and diseases [8–10]. Previous studies suggested that the optimal temperature for greenhouse crops ranged from 18.5 to $26.5\text{ }^{\circ}\text{C}$, with day and night temperatures maintained between 21 and $29.5\text{ }^{\circ}\text{C}$ and 18.5 to $21\text{ }^{\circ}\text{C}$, respectively. According to the standards of ASABE (2015), the suitable relative humidity for most greenhouse tomato varieties was between 60% and 90%. Previous studies also showed that tomato pollination was significantly enhanced when relative humidity was approximately 60%. In many developing countries, more than two-thirds of protected cultivation took place in low-technology facilities. Consequently, these facilities had a poor ability to regulate and resist adverse meteorological conditions [4,11]. Irrigation is the sole source of water required to sustain greenhouse crops. As is well-known, the irrigation demand of crops grown in greenhouses varies with their growth stages. Generally, the water demand is relatively low during the seedling stage, reaches its peak during the fruiting stage, and then decreases in the late growth stage [1]. Therefore, how to optimize the combination of irrigation amount and temperature patterns becomes a key challenge restricting the achievement of high yield and high-quality greenhouse crops.

Crop models are important predictive tools, and are often used to simulate crop growth and assess the impact of various factors on crop planting dates, varieties, nitrogen, and water management [12,13]. Using appropriate crop models under varying conditions

can effectively improve the prediction of key crop indicators. This not only has proved to be an effective and time-saving approach, but also has become indispensable in modern agriculture [14,15]. Among them, AquaCrop and DSSAT are two of the most widely applied models: AquaCrop is a water-driven model developed by the FAO, with a concise interface and relatively few parameters [16], whereas DSSAT is radiation-driven and represents crop growth mainly through photosynthesis and carbon partitioning [17]. To date, both models have also been shown to perform well in simulating greenhouse crops under ambient temperature conditions. For example, Shan et al. [18] used the DSSAT-CROPGRO-Tomato model to simulate the growth, water consumption and yield under different water and nitrogen regimes. Wu et al. [19] calibrated the AquaCrop model under coupled water, fertilizer, and biochar conditions and, in combination with the NSGA-II multi-objective optimization algorithm, identified an optimal management strategy that could synergistically enhance greenhouse tomato yield and water productivity while conserving water and fertilizer. In addition, several studies have directly compared the two models; for example, Wang et al. [15] evaluated AquaCrop and DSSAT-SUBSTOR-Potato for simulating potato growth, yield, and water productivity under different drip-fertigation regimes, and found that AquaCrop generally gave higher accuracy than DSSAT. Similarly, Ge et al. [20] compared AquaCrop and DSSAT for greenhouse drip-irrigated tomato under different irrigation modes. However, these studies were mostly conducted under ambient temperature, and the performance of the two models under controlled high-temperature conditions in greenhouses has received little attention.

To address the aforementioned issues, we hypothesized that crop models can accurately capture the interactive effects of varying water and temperature conditions on greenhouse-grown tomatoes, thereby enabling the identification of an optimal environmental management strategy that maximizes yield and water use efficiency. To test this hypothesis, the specific objectives of our study were to: (1) calibrate and validate the AquaCrop and DSSAT models under varying water and temperature conditions in greenhouse-grown tomatoes; (2) evaluate the performance of the AquaCrop and DSSAT models in simulating canopy cover, soil water content, above-ground biomass, yield, water consumption, and water use efficiency; and (3) obtain the optimal water and temperature combination by setting 20 possible scenario modes.

2. Materials and Methods

2.1. Experimental Site

The experiment was conducted from March to June in 2024 and 2025 at the Water-Saving Key Laboratory in Henan Province (34°47' N, 113°39' E; elevation 80 m). This region is characterized by a temperate continental monsoon climate, with unevenly distributed annual rainfall, most of which occurs in July and August. The average annual precipitation is 548 mm, the average annual evaporation is 1909 mm, the average annual frost-free period is 209 days, and the average annual air temperature is 14 °C. Soil type and hydraulic properties of the 0–60 cm soil layer in the experimental area are presented in Table 1.

Table 1. Soil types and hydraulic parameters of the 0–60 cm soil layer inside the greenhouse.

Depth (cm)	Particle Composition/%			BD (g/cm ³)	FC (cm ³ /cm ³)	WP (cm ³ /cm ³)	SOC (%)	pH	θ_s (cm ³ /cm ³)	K_s (cm/d)
	Clay	Silt	Sand							
0–20	21.6	78.4	0	1.47	0.306	0.0806	1	8.47	0.4105	45.60
20–40	21.4	78.6	0	1.44	0.2749	0.0952	0.5	8.8	0.4209	25.13
40–60	20.8	78	1.2	1.52	0.3191	0.0931	0.5	8.82	0.4578	55.56

BD is the soil bulk density; FC is the field capacity; WP is the wilting point; SOC is the soil organic carbon; θ_s is the saturation water content; K_s is the saturated hydraulic conductivity.

2.2. Experimental Design

The greenhouse used in the experiment covered an area of 70 m² (10 m × 7 m), featured a steel frame structure, and was covered with a single layer of polyethylene film. The tomato variety “Jingfan 404” was transplanted on 19 March 2024, and 15 March 2025, respectively, following a planting pattern of wide rows (0.65 m) alternating with narrow rows (0.45 m). Prior to transplantation, each plot received 0.583 t·ha^{−1} of compound fertilizer, and during the fruit expansion stage of each truss, an additional 0.625 t·ha^{−1} of water-soluble fertilizer was applied. On the day of transplantation, 20 mm of water was applied to ensure seedling survival, and black polyethylene film was used to cover the soil surface to maintain seedling temperature.

High-temperature and ambient-temperature treatments were conducted in two adjacent, structurally identical greenhouses. The experiment was arranged as a split-plot design, with temperature as the main-plot factor and water as the sub-plot factor. Within each greenhouse, each water treatment was replicated in three plots. In any given year, each temperature level was assigned to one greenhouse; to reduce the risk that the temperature effect would be confounded with a specific greenhouse, the two temperature treatments were rotated between the greenhouses across the two years, with greenhouse 1 assigned to the high-temperature treatment in 2024 and greenhouse 2 in 2025. Two temperature treatments were applied. The *TH* was designed such that the daily maximum air temperature was no lower than 35 °C and no higher than 40 °C, whereas the *TD* was designed with a daily maximum air temperature no higher than 35 °C. The two water treatments were full irrigation (*WH*, 100%*E_{pan}*) and deficit irrigation (*WD*, 60%*E_{pan}*), where *E_{pan}* is the cumulative pan evaporation. The experimental design can be referred to in [21–23]. No temperature or water treatments were applied during the seedling stage to allow for seedling acclimation. The controlled temperature and water treatments were implemented once the plants reached the flowering and fruit-setting stage.

Temperature variation inside the greenhouse was regulated by a BY-WSK IoT-based intelligent greenhouse control system (Henan Bangyou Hi-Tech Co., Zhengzhou, China). The system consisted of a main control unit, distributed temperature sensor modules, and an air-cooled compression refrigeration unit. Temperature sensors were installed at crop canopy height to collect multi-point temperature data in real time and transmit them to the main control unit. During the experiment, when the external temperature reached 35 °C, the control system automatically activated the cooling program and updated the temperature data every 5 min.

Irrigation management was based on the cumulative evaporation from a standard 20 cm diameter evaporation pan, which was positioned 30 cm above the crop canopy. Irrigation was applied when the cumulative evaporation from the pan reached 10 ± 2 mm. Drip irrigation was used, with drippers spaced 30 cm apart and a flow rate of 1.1 L h^{−1}. A drip tape was laid along each row of plants, with each plot’s drip tape connected to a sub-main pipe. Each sub-main was equipped with a water meter with an accuracy of 0.001 m³. All sub-mains were connected to the main pipe, which was fitted with a total water meter and a pressure gauge. Other agronomic practices in the greenhouse, such as pesticide application, topping, and weeding, were conducted following local standard procedures.

2.3. Measurements and Methods

An automated weather station was installed at the center of each greenhouse to monitor meteorological parameters. Air temperature (*T_a*) and relative humidity (*RH*) were measured at 2 m above the ground and at crop canopy height using HOBO RS3-B and U23 Pro v2 loggers (Onset Computer Corporation, Bourne, MA, USA). Total solar radiation (*R_s*) was recorded with a LI-200X pyranometer (Campbell Scientific, Inc., Logan,

UT, USA), net solar radiation (R_n) with an NR-LITE2 net radiometer (Kipp & Zonen, Delft, The Netherlands), and wind speed with a WindSonic ultrasonic anemometer (Gill Instruments Ltd., Lymington, Hampshire, UK). Sensors were positioned at 2 m, and data were recorded every 5 s, averaged over 15 min, and then stored in a CR1000 logger (Campbell Scientific, Inc., Logan, UT, USA). Figure 1 shows temperature variations under two treatments and corresponding reference evapotranspiration (ET_0) trends.

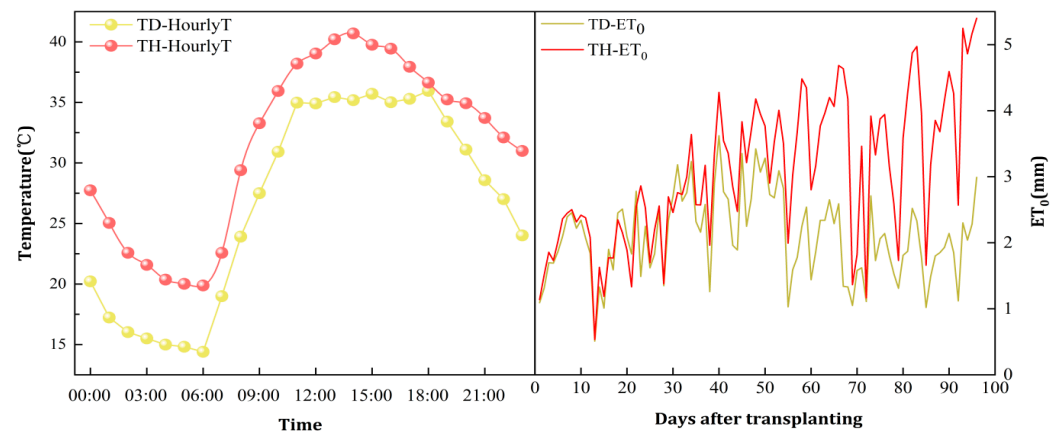


Figure 1. Variations in temperature and reference crop evapotranspiration inside the greenhouses under the two temperature treatments.

Soil water content (SWC) was measured using a TRIME-IPH (IMKO, Germany) time domain reflectometer. The measuring tube was installed at the midpoint between two plants, and SWC was measured at depths of 10, 20, 30, 40, and 60 cm below the soil surface every 7–10 days. Each treatment was replicated three times. To minimize errors, the instrument was regularly calibrated using the soil drying method.

Six plants with similar growth and good status were randomly selected, and leaf area was measured every 7–10 days. Leaf area was estimated using a length–width regression method. For each leaf, the rectangular area (maximum longitudinal length $\times$ maximum transverse width) was multiplied by a reduction coefficient of 0.64 and summed over all leaves. This coefficient was obtained by fitting the measured leaf areas to those delineated using CAD software (version 2020, Autodesk Inc., San Rafael, CA, USA), following our previous study in the same solar greenhouse [24]. The leaf area index (LAI) was calculated as follows:

$$LAI = 0.64 \sum L \times W / (S_l \times S_r) \quad (1)$$

where L was the leaf length (cm), W was the leaf width (cm), S_l was the row spacing (cm), and S_r was the plant spacing (cm). The canopy cover (CC) was estimated from the LAI following the empirical exponential relationship based on the Beer–Lambert law adopted in the FAO AquaCrop framework [25], expressed as follows:

$$CC = 1.005 \times \left[1 - e^{(-0.6LAI)} \right]^{1.2} \quad (2)$$

Evapotranspiration (ET) was calculated using the water balance method, expressed as follows:

$$ET = P + I_r + U - R - D \pm \Delta W \quad (3)$$

where P is the precipitation (mm); I_r is the irrigation amount (mm); U is the groundwater recharge (mm); R is the surface runoff (mm); D is the deep percolation (mm); and ΔW is the change in water storage in the 0–60 cm soil layer (mm).

Owing to the shielding effect of the greenhouse plastic film, the precipitation inside the greenhouse was zero. The groundwater table in the study area remained below 5 m year round, so the groundwater recharge was zero. Under drip irrigation, the irrigation amount was small (the maximum single application was 22 mm); therefore, both surface runoff and deep percolation were zero. Accordingly, the simplified water balance equation is as follows:

$$ET = I_r - \Delta W \quad (4)$$

Water use efficiency (WUE , $\text{kg} \cdot \text{m}^{-3}$) can be calculated using the following formula:

$$WUE = Y/ET \times 100 \quad (5)$$

where Y was the tomato yield ($\text{t} \cdot \text{ha}^{-1}$).

3. Model Introduction and Parameter Calibration

3.1. Introduction of the AquaCrop Model

AquaCrop is a general model. Its input requirements encompass four primary components: weather data, crop specifications, soil characteristics, and management practices [26]. Weather data, sourced from field observation or weather stations, comprises critical variables such as minimum and maximum air temperature, ET_0 , rainfall, and carbon dioxide concentrations. Regarding crop characteristics, users are prompted to select an appropriate canopy development approach tailored to specific conditions which could be based on calendar days or growing degree days ($GDDs$). Additionally, crop development is divided into four phases: initial canopy cover, canopy development, flowering and yield formation, and root deepening. The computation of actual ET involves the partitioning of water use into soil evaporation and crop transpiration, as indicated by Equation (6). This particular aspect of the model is noteworthy because it divides water use into productive and inefficient use, a division that helps more accurately model the water yield relationship.

The production module encompasses metrics such as crop water productivity and harvest index [25,27–29]. In the water module, the main factors influencing crop canopy expansion are considered, including canopy expansion itself, stomatal closure, accelerated canopy senescence, and altered harvest index. In Equation (6), the green canopy cover CC is adjusted to an effective value CC^* to account for micro-advective effects on transpiration. When the canopy is incomplete, the transpiration per unit ground area covered is higher than that of a fully closed canopy, because sensible heat is advected from the surrounding drier or bare soil surfaces to the sparse canopy (the so-called “clothes-line” or “oasis” effect). AquaCrop represents this enhancement through the adjustment $CC^* = 1.72 \cdot CC - CC^2 + 0.30 \cdot CC^3$, so that transpiration is slightly increased at low canopy cover and converges to CC as the canopy closes. These factors respond to the influence of water availability. To account for climatic conditions, AquaCrop employs the concept of normalized water productivity when simulating above-ground biomass (AB). Normalization aims to render crop water productivity applicable across diverse locations, seasons, and even future climate scenarios (Equation (7)). The final yield is then determined from biomass and the harvest index using Equation (8).

$$T_r = CC^* \times K_{cTr,x} \times ET_0 \quad (6)$$

$$B = WP^* \times \sum_{i=1}^n \frac{T_{ri}}{ET_{oi}} \quad (7)$$

$$Y = f_{HI} \times HI_0 \times B \quad (8)$$

where CC^* was the actual canopy cover (%) adjusted by the micro advection effect; $K_{cTr,x}$ was the maximum standard crop transpiration coefficient; B was biomass in $t \cdot ha^{-1}$; WP^* was the normalized crop water productivity in $g \cdot m^{-2}$; T_{ri} and ET_{oi} were the crop transpiration ($mm \cdot day^{-1}$) and reference evapotranspiration ($mm \cdot day^{-1}$) of the i th day; Y was tomato fresh fruit yield in $t \cdot ha^{-1}$; f_{HI} was the harvest index; and HI_0 was the reference harvest index.

The AquaCrop model was developed on the foundation of mathematical functions, specific variables, and parameters. To enhance and evaluate its performance, many parameters must be calibrated to accurately simulate some indicators such as biomass, canopy cover, and yield [13,30]. Consequently, these parameters of the model can be classified into two categories: conservative parameters and non-conservative parameters. Non-conservative parameters, unaffected by climatic variations and management strategy, can be directly adopted from the reference manual’s specific crop values. Conversely, conservative parameters must be fine-tuned within the range of the manual using a trial-and-error methodology, as discussed by [31]. In our study, we sourced temperature and ET_0 data from an automatic weather station located in the greenhouse. ET_0 was calculated using the Penman–Monteith equation, as outlined in [32]. Additionally, the CO_2 concentration was selected from the concentration-IPCC: RCP4.5 dataset, as referenced from [33]. Furthermore, for a comprehensive understanding of the parameter settings process, refer to [31]. Generally, AquaCrop parameter validation and calibration require data from different years to ensure model accuracy [34].

In this study, the AquaCrop parameters (Table 2) were calibrated by trial-and-error, while all other crop parameters were kept at their default values. The parameters were not adjusted simultaneously but sequentially, following the crop growth sequence: canopy-related parameters (e.g., CC_x , CGC) were tuned first to match the observed canopy cover, followed by biomass- and yield-related parameters (e.g., WP^* , HI_0), and finally the parameters affecting evapotranspiration. The parameters were adjusted iteratively until no further improvement could be obtained in the overall agreement across the target variables. Calibration was based on the well-watered, ambient-temperature treatment (TDWH) in 2024. The calibrated parameter set was then applied without further adjustment to the remaining treatments in 2024 (cross-treatment validation) and to all treatments in 2025 (cross-year validation), so that the 2025 data served as a fully independent validation set.

Table 2. Calibration of the AquaCrop model parameters for tomato grown in the greenhouse.

Crop Parameters	Descriptions	Unit	Initial Value	Calibrated Values
CC_0	Initial canopy coverage	%	0.67	1.2
CGC	Canopy expansion	$\% d^{-1}$	12.3	15.0
CC_x	Maximum canopy cover	%	75	89
CDC	Canopy decline	$\% d^{-1}$	7.2	12.8
Recovered	Transplanting to recovered	d	4	5
Time to CC_x	Transplanting to CC_x	d	63	64
Senescence	Transplanting to senescence	d	93	92
Maturity	Transplanting to maturity	d	110	111
$K_{cTr,x}$	Crop transpiration	/	1.10	1.25
WP^*	Water productivity	$g m^{-2}$	18	18
HI_0	Reference harvest index	%	63	59
$K_{s_{exp,w}}$ (upper)	Soil water depletion threshold for canopy expansion-upper	/	0.15	0.25
$K_{s_{exp,w}}$ (lower)	Soil water depletion threshold for canopy expansion-lower	/	0.55	0.6
Shape factor	Shape factor for water stress coefficient for canopy expansion	/	3	3
$K_{s_{sto}}$ (upper)	Soil water depletion threshold for stomatal control-upper threshold	/	0.5	0.5
Shape factor	Shape factor for water stress coefficient for stomatal control	/	3	3
$K_{s_{sen}}$ (upper)	Soil water depletion threshold for canopy senescence-upper	/	0.7	0.5
Shape factor	Shape factor for water stress	/	3	3
Base temperature	Threshold temperatures for crop development	$^{\circ}C$	7	10
Upper temperature	Threshold temperatures for crop development	$^{\circ}C$	28	35

3.2. Introduction of the DSSAT Model

In the DSSAT (Decision Support System for Agrotechnology Transfer) model, the main input data include meteorological data, soil data and management data. The key meteorological data include daily maximum and minimum temperature, daily solar radiation and rainfall. It also allows users to add wind speed, photosynthetically active radiation (PAR) and other parameters, depending on data availability, to improve model simulation accuracy. In the DSSAT model, soil water supply to plants is simulated through daily processes; because the model requires soil to be layered during data input, the daily change in SWC for each layer is calculated using the water balance formula, see Equation (3).

In terms of water balance simulation, the model analyzes crop water supply dynamics using a layered soil module architecture, coupling core parameters such as vegetation cover index to assess their regulatory effects on water content in different soil layers, while simultaneously considering water movement and redistribution within the soil profile [35]. Water redistribution is triggered after soil saturation; when SWC is between the wilting point and field capacity, water availability is jointly determined by wilting coefficient, field capacity, and actual water content. For water consumption calculation, the currently used methods are mainly the FAO-56 Penman–Monteith equation or the Priestley–Taylor model, which differ significantly in data requirements and calculation accuracy [36]. The Priestley–Taylor model only requires daily maximum and minimum temperatures and solar radiation, whereas the Penman–Monteith equation needs additional daily data of relative humidity and wind speed. Therefore, the Priestley–Taylor model was adopted for calculating crop water consumption.

CROPGRO is an important module in the DSSAT model, and its calculation of dry matter accumulation is mainly based on the carbon balance principle. The model first calculates the PAR intercepted by the canopy, then the gross primary productivity, and subtracts the maintenance respiration; the remaining carbohydrates are then converted into structural dry matter according to a given conversion efficiency Equation (9). Different from the AquaCrop model, CROPGRO uses *LAI* to represent the crop growth level; the growth of *LAI* is jointly controlled by temperature, energy supply and water stress. In the later stage, *LAI* will decrease due to physiological senescence, low temperature or stress Equation (10). In the CROPGRO model, dry matter is distributed to each organ according to phenological stage. After flowering and fruit setting, the fruit becomes the main carbon sink. The final fresh fruit yield depends on the accumulated fruit dry matter and the water content of tomato fruits Equation (11).

$$\Delta W = E_g \times (P_g - R_m) \times f(W, N) \quad (9)$$

where ΔW is the daily potential new dry matter production; E_g was the growth conversion efficiency; P_g was daily gross canopy photosynthesis; R_m was maintenance respiration; and $f(W, N)$ was water and nitrogen stress factor.

$$\Delta LAI = (\Delta B_{leaf} \times SLA) - \Delta LAI_{senescence} \quad (10)$$

where B_{leaf} was the daily biomass partitioned to leaves; *SLA* was the specific leaf area; and $\Delta LAI_{senescence}$ was the senesced leaf area.

$$Y_{fresh} = \frac{\sum(\Delta W \times X_{fruit})}{1 - WC_{fruit}} \quad (11)$$

where X_{fruit} was the fraction of dry matter partitioned to fruit on day, *t*. WC_{fruit} is the average water content fraction of the harvested tomato fruits.

Accordingly, the DSSAT-CROPGRO-Tomato model was calibrated using the TDWH in 2024, which was free of water stress as required for reliable estimation of genetic coefficients. The four development-stage coefficients (EM-FL, FL-SH, FL-SD, and SD-PM) were set based on cultivar characteristics, field observations, and reference values, and were not estimated by Generalized Likelihood Uncertainty Estimation (GLUE). The remaining growth- and yield-related coefficients (LFMAX, SLAVR, XFRT, SFDUR, PODUR, and THRESH) were estimated using the GLUE module, a Bayesian procedure that draws parameter sets from prior distributions through Monte Carlo sampling and selects the set that best reproduces the observations. The measured leaf area index, above-ground biomass, and yield were used as calibration targets, with 50,000 model runs. The calibrated coefficients (Table 3) were then applied without further adjustment to the remaining treatments in 2024 (cross-treatment validation) and to all treatments in 2025 (cross-year validation), so that the 2025 data served as a fully independent validation set.

Table 3. Calibration of the DSSAT model parameters for greenhouse tomato in the greenhouse.

Crop Parameters	Descriptions	Unit	Initial Value	Calibrated Values
EM-FL	Time from germination to the appearance of the first flower in terms of light and heat.	°C·d	7–35	23.95
FL-SH	Time from the first inflorescence flowering to the first inflorescence setting fruit in terms of light and heat.	°C·d	7–9	8.42
FL-SD	Time from the first inflorescence flowering to the first inflorescence seed production in terms of light and heat.	°C·d	15–20	19.55
SD-PM	Time from the first inflorescence seed production to physiological maturity in terms of light and heat.	°C·d	45–55	48.02
LFMAX	Maximum photosynthetic rate of leaves under optimum conditions (measured in terms of CO ₂).	mg·m ² ·s ^{−1}	1–1.4	1.40
SLAVR	Specific leaf area.	cm ² ·g ^{−1}	320–380	325
XFRT	Maximum proportion of dry matter allocated to fruits per day.	/	0.65–0.85	0.71
SFDUR	Duration of seed filling in fruits in terms of light and heat.	°C·d ^{−1}	23–27	24.96
PODUR	Time required for optimal conditions to achieve the final fruit load in terms of light and heat.	°C·d ^{−1}	40–65	57.66
THRESH	Threshing percentage: the maximum ratio of total pod/fruit dry matter at maturity.	/	7–10	8.90

3.3. Scenario Simulation Setup

The scenario analysis was based on the AquaCrop model for the following reasons. First, in the calibration and validation against the two-year measurements, AquaCrop simulated the observed crop and water dynamics with slightly higher accuracy than DSSAT-CROPGRO-Tomato under the high-temperature conditions of this study for most indicators (Sections 5 and 6.5). As discussed in Section 6.5, this is attributed to the consistency between its water-driven structure and the dominant heat–water stress pathway in this system, rather than to a general superiority of one model over the other. Using the model with higher accuracy under these conditions provides a more reliable basis for extrapolation to untested temperature–water combinations. Second, AquaCrop has a relatively simple structure and low input requirements, and its applicability under limited-data conditions has been widely reported [37]; it is therefore more suitable for scenario simulations under hypothetical conditions where meteorological data are relatively scarce. Third, the required inputs were generated using a temperature-driven XGBoost model. ET_0 is closely correlated with temperature and can be predicted from temperature with acceptable accuracy, whereas solar radiation, which is required by DSSAT-CROPGRO-Tomato, is mainly governed by extraterrestrial radiation and cloudiness and is far less sensitive to temperature, so its

prediction from temperature alone would be less reliable. As AquaCrop is driven directly by ET_0 , it is readily compatible with this approach.

To clarify the optimal temperature and irrigation combination strategy for greenhouse crops, our study sets up multiple scenarios to analyze the effects of different temperature and water combinations on crop yield and water use efficiency. The specifics are as follows: temperature and water were defined as the core regulatory variables, and based on the 2025 experimental data, temperature was set at five gradient levels (32 °C, 34 °C, 36 °C, 38 °C and 40 °C), and water at four gradient levels ($0.5E_{pan}$, $0.7E_{pan}$, $0.9E_{pan}$ and $1.1E_{pan}$), for a total of 20 combination treatments, as shown in Table 4.

Table 4. Combination of different temperature and soil water content scenarios.

Combination Code	32 °C	34 °C	36 °C	38 °C	40 °C
$0.5E_{pan}$	C1	C5	C9	C13	C17
$0.7E_{pan}$	C2	C6	C10	C14	C18
$0.9E_{pan}$	C3	C7	C11	C15	C19
$1.1E_{pan}$	C4	C8	C12	C16	C20

Rows represent different temperature gradients, and columns represent different moisture gradients.

The temperature range (32–40 °C) was chosen to represent the microclimate actually observed in the naturally ventilated greenhouse during the spring–summer season, rather than projected future climates or the acute (>40 °C) heat stress typically imposed in growth chambers; it reflects the long-term, moderate-to-severe heat stress that greenhouse tomato experiences in summer. The lower bound was set at 32 °C rather than 30 °C because, in a solar greenhouse in Zhengzhou during spring and summer, the indoor temperature does not fall below about 32 °C even with active cooling; the upper bound of 40 °C corresponds to the temperature at which tomato flowering and fruit set are severely impaired. Accordingly, the scenario grid implicitly assumes that radiation, humidity, and wind speed remain at their 2025 levels while temperature is varied; the results therefore represent the response to temperature under baseline meteorological conditions. The four irrigation levels (0.5, 0.7, 0.9, $1.1E_{pan}$) bracket the two experimental treatments (WD = 0.6, WH = $1.0E_{pan}$), with $1.1E_{pan}$ included to test whether irrigation above full replacement provides any further yield benefit.

Although the scenario simulation is based on the 2025 experiment, the introduction of multiple temperature gradients requires recalculation of an essential input parameter, ET_0 , because the ET_0 values measured in 2025 cannot be directly applied to other temperature gradients. To address this, the XGBoost model was employed to predict ET_0 for the different treatment combinations, as previous studies have demonstrated that XGBoost can effectively predict ET_0 . The XGBoost method, developed by Chen and Guestrin [38], is an ensemble decision-tree algorithm based on the Gradient Boosting Decision Tree (GBDT) framework. Using a boosting approach, it integrates decision trees as base learners to form a “strong” learner. The core concept is that during training, each new decision tree is generated to fit the residuals of the previous tree, thereby improving model accuracy. In other words, at each training iteration, a weak model f_k is constructed as a decision tree, and after N iterations, the final output is obtained by summing the results of all N weak models. This process can be expressed as follows:

$$y_i = \sum_{k=1}^N f_k(x_i) \quad (12)$$

In the equation, y_i was the predicted value; f_k was the k-th decision tree; x_i was the i-th sample; and N was the total number of decision trees.

The objective function of the XGBoost model consists of a loss function, which aims to improve predictive accuracy, and a regularization term, which was incorporated to mitigate the risk of over-fitting. The objective function used to determine the structure of the decision trees during XGBoost model training is expressed as follows:

$$Obj = \sum_{i=1}^n l(\hat{y}_i, y_i) + \sum \Omega(f_t) \quad (13)$$

$$\Omega f_t = \gamma T + \frac{1}{2} \lambda \sum_{j=1}^T W_j^2 \quad (14)$$

where γ is the complexity penalty per additional leaf, T is the number of leaves in the tree, λ is the L2 regularization coefficient, and W_j is the weight (output score) of the j -th leaf.

In this expression, n denotes the total number of samples, $L(\hat{y}_i, y_i)$ represents the loss corresponding to a single sample, $\hat{y}_i$ is the predicted value generated by the model, and y_i is the measured value of the sample. The term $\sum \Omega(f_t)$ stands for the regularization term. Furthermore, during the derivation of the loss function, the XGBoost model incorporates both first-order and second-order derivative information, a design that substantially improves the convergence efficiency of the model.

Zhu and Qing screened factors exhibiting strong correlations with ET_0 by means of Pearson's correlation analysis [39]. Among these factors, T_{max} , T_{min} , and T_{mean} all showed extremely significant correlations with ET_0 . Moreover, because temperature was prescribed as a set of hypothetical gradients in the scenario simulations, the other meteorological drivers of ET_0 (solar radiation, vapor pressure deficit, and wind speed) could not be determined consistently for these settings, so temperature was the only variable available across all scenarios. Temperature-based ET_0 estimation also has an established basis: the Hargreaves equation, which uses only air temperature and extraterrestrial radiation, is recognized by FAO as a substitute for Penman–Monteith when full meteorological inputs are unavailable [40,41]. For these reasons, T_{max} , T_{min} , and T_{mean} were used as inputs.

In terms of implementation, the model was developed in Python 3.10.1 using the xgBoost (version 3.2.0) and scikit-learn (version 1.8.0) libraries, with the Penman–Monteith ET_0 as the prediction target. Because the 2024 and 2025 tomato seasons alone provided a limited sample, the training data were extended to cover four years (2022 to 2025); these data were obtained from the same greenhouse, under the same experimental treatments, and with the same cultivar, ensuring that the combined dataset was homogeneous. T_{max} , T_{min} , and T_{mean} were used as inputs and the Penman–Monteith ET_0 as the target. The dataset contained 1000 daily ET_0 values from four growing seasons (2022 to 2025) under the two temperature treatments, and was randomly split into 80% for training and 20% for validation. As all samples came from the same site and consecutive seasons, this random split reflects internal validation rather than independent temporal validation. Hyperparameters were tuned by grid search with five-fold cross-validation, using the negative mean squared error as the selection criterion. The search space covered the number of estimators (100, 200, 300), maximum tree depth (3, 5, 7), learning rate (0.01, 0.05, 0.1), subsample ratio (0.8, 1.0), column subsample ratio (0.8, 1.0), and gamma (0, 0.1), and the optimal combination was selected automatically within this space. Model performance is reported in Figure 2. The results demonstrate that the overall prediction accuracy remains at an acceptable level ($p < 0.01$, $RMSE < 0.55$), on the basis of which ET_0 values corresponding to different temperature gradients were derived.

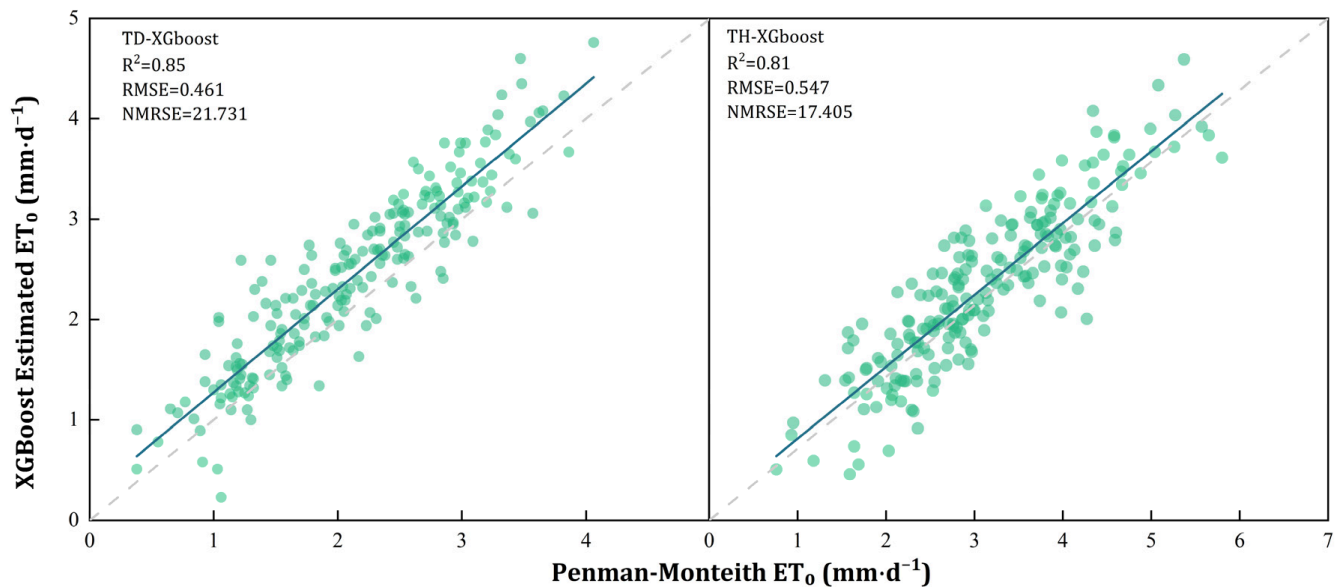


Figure 2. Performance of XGBoost model in estimating ET_0 vs. Penman–Monteith.

4. Performance Evaluation of Two Models

Root mean square error ($RMSE$), normalized root mean square error ($NRMSE$), and efficiency coefficient (EF) were selected to evaluate the performance of the AquaCrop and DSSAT models. $RMSE$, which operates within a range of 0 to infinity, indicates the average error between observed and simulated values. Smaller $RMSE$ values correspond to better simulation accuracy. $NRMSE$ assesses the normalized $RMSE$ value and was classified into four grades (excellent, values < 10%; good, 10–20%; acceptable, 20–30%; poor > 30%) [42]. EF and R^2 were also used, with values closer to 1 indicating a higher model performance. The expression for these statistical indices is as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (S_i - O_i)^2} \quad (15)$$

$$NRMSE = \frac{RMSE}{\bar{O}} \times 100 \quad (16)$$

$$EF = 1 - \frac{\sum_{i=1}^n (S_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \quad (17)$$

$$R^2 = \left(\frac{\sum_{i=1}^n (O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2 \sum_{i=1}^n (S_i - \bar{S})^2}} \right)^2 \quad (18)$$

where n was the number of observations, S_i and O_i were the simulated and observed values, respectively, in terms of $\bar{S}$ and $\bar{O}$, which were the means of simulated and observed values, respectively.

5. Results

5.1. Canopy Cover (CC)

Figure 3 compares the measured and simulated canopy cover (CC) of greenhouse tomato under the different temperature and water treatments. Under ambient temperature (TD), both AquaCrop and DSSAT-CROPGRO reproduced CC well under both irrigation levels, with high agreement across all statistical indicators (Table 5). Under high temperature (TH), AquaCrop maintained its accuracy under full irrigation (WH), whereas DSSAT-CROPGRO

performed slightly worse; under water deficit (WD), both models overestimated CC, with DSSAT-CROPGRO overestimating more than AquaCrop (10.18% vs. 6.98%).

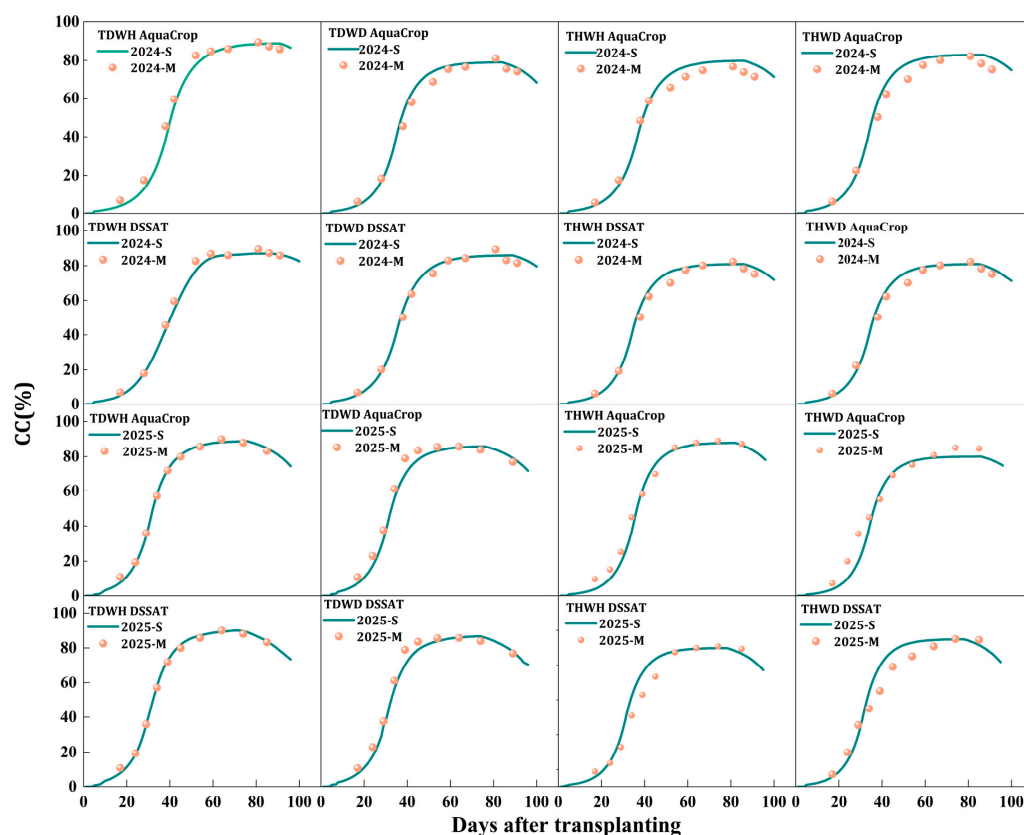


Figure 3. Correlations of greenhouse tomato canopy cover (CC) between measured and simulated under varying water and temperature conditions in 2024, 2025. M was measured values and S was simulated values.

Table 5. Statistical indicators of canopy cover (CC) comparing that simulated by two models and measurements under varying water and temperature conditions.

Year	Treatments	Models	R^2	RMSE	NRMSE	EF
2024	TDWH	AquaCrop	0.99	2.92	4.14	0.99
		DSSAT	0.99	3.12	4.87	0.98
	TDWD	AquaCrop	0.97	3.84	6.02	0.97
		DSSAT	0.98	2.65	4.16	0.98
	THWH	AquaCrop	0.97	4.93	7.95	0.98
		DSSAT	0.97	3.39	5.64	0.98
	THWD	AquaCrop	0.95	4.98	8.23	0.96
		DSSAT	0.97	3.51	5.81	0.96
2025	TDWH	AquaCrop	0.99	1.49	2.39	0.99
		DSSAT	0.99	1.42	2.28	0.99
	TDWD	AquaCrop	0.98	4.78	7.62	0.94
		DSSAT	0.99	4.15	6.62	0.94
	THWH	AquaCrop	0.98	4.09	7.86	0.97
		DSSAT	0.91	6.72	12.92	0.94
	THWD	AquaCrop	0.97	6.84	12.27	0.92
		DSSAT	0.92	7.24	12.99	0.95

These results indicate that for CC simulation, both models are less accurate under THWD than under THWH. A possible explanation is related to the model parameters: in AquaCrop, $K_{s_{exp,w}}$, and in DSSAT-CROPGRO, SLAVR, were calibrated based on well-

watered conditions, enabling better alignment with crop growth characteristics under sufficient soil moisture. However, high temperature combined with water deficit accelerates stress-induced senescence, and since model parameters were calibrated under normal temperature conditions, they may be too conservative to capture the rapid decline caused by combined stress, leading to delayed responses in the simulated CC under THWD.

5.2. Soil Water Content

Figure 4 compares the simulated and observed SWC of greenhouse tomato using the AquaCrop and DSSAT-CROPGRO models. Overall, both models performed within an acceptable range, although they slightly overestimated SWC during the early growth stage, approximately the first 40 days after transplanting. Under ambient temperature (TD), both models simulated SWC satisfactorily, with the highest accuracy under full irrigation (WH); AquaCrop slightly outperformed DSSAT-CROPGRO, and accuracy under water deficit (WD), although slightly reduced, remained reasonable (Table 6). However, under high temperature (TH), simulation accuracy for SWC declined markedly, with R^2 dropping to 0.33 and 0.27 for AquaCrop and DSSAT-CROPGRO, respectively, and EF even reaching negative values. The weakest performance occurred when high temperature and water deficit co-occurred, giving the lowest accuracy across all treatments (Table 6). These results indicate that, although both models can reproduce the dynamics of soil water content under different water treatments at ambient temperature, their simulation capability decreases during the early growth stage and, in particular, under the combination of high temperature and water deficit, in some cases to the point where the models are almost ineffective. This highlights the limitations of the current model formulations in representing rapid changes in soil water availability under high-temperature greenhouse conditions.

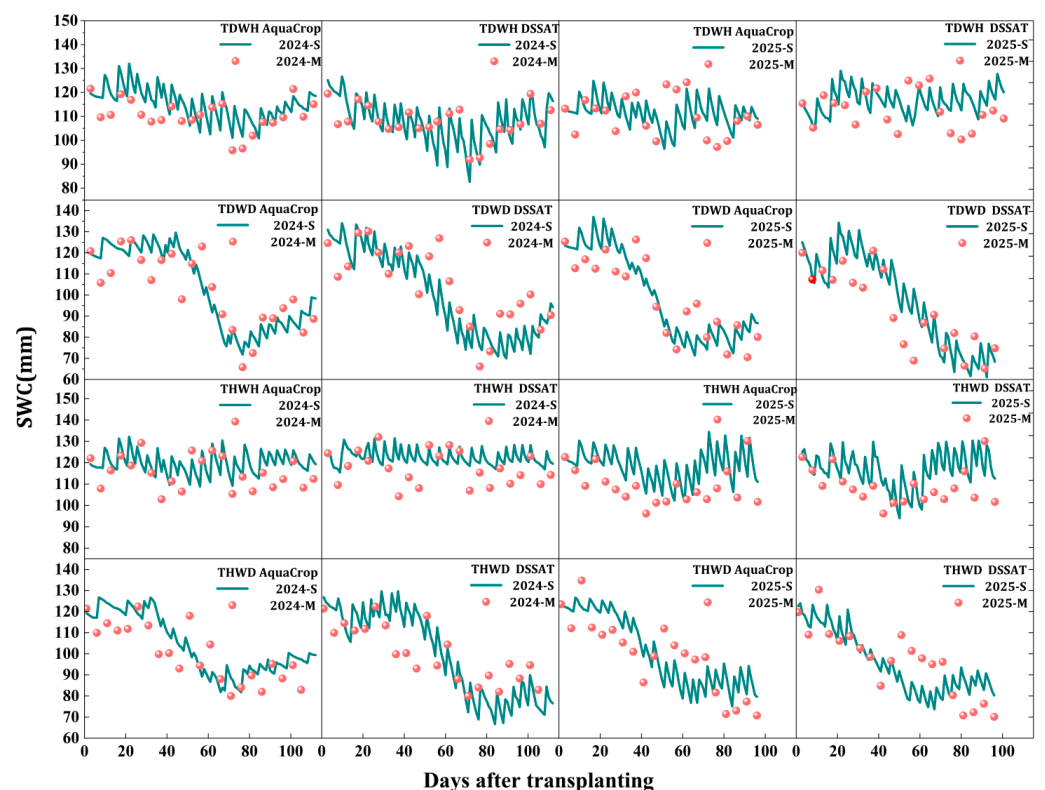


Figure 4. Correlations of soil water content (SWC) in the 0–60 cm soil layer between measured and simulated under varying water and temperature conditions in 2024, 2025. M was measured values and S was simulated values.

Table 6. Model fit indicators for soil water content (SWC) at depth of 0–60 cm under varying water and temperature conditions in 2024 and 2025.

Year	Treatments	Models	R^2	RMSE	NRMSE	EF
2024	TDWH	AquaCrop	0.72	6.89	6.24	0.36
		DSSAT	0.79	5.50	4.98	0.42
	TDWD	AquaCrop	0.71	13.18	13.08	0.52
		DSSAT	0.70	13.68	13.58	0.52
	THWH	AquaCrop	0.55	12.54	10.98	0.32
		DSSAT	0.54	13.21	11.58	0.27
	THWD	AquaCrop	0.56	14.87	15.24	0.26
		DSSAT	0.48	14.57	14.54	0.33
2025	TDWH	AquaCrop	0.79	9.01	7.73	0.62
		DSSAT	0.77	12.15	10.34	0.49
	TDWD	AquaCrop	0.65	11.58	12.23	0.68
		DSSAT	0.64	13.46	12.27	0.48
	THWH	AquaCrop	0.57	12.55	13.78	−1.66
		DSSAT	0.55	14.64	13.86	−1.68
	THWD	AquaCrop	0.33	14.10	14.44	0.43
		DSSAT	0.27	15.79	14.12	0.46

5.3. Yield, Above-Ground Biomass, Water Consumption and Water Use Efficiency

Measured and simulated values of yield, above-ground biomass (AB), water consumption (ET), and water use efficiency (WUE) of greenhouse tomato under different temperature and water combinations, along with their deviations, are presented in Table 7. Regarding yield, both the AquaCrop and DSSAT-CROPGRO models performed better under normal temperature TD than under high temperature TH, although accuracy under TH remained within an acceptable range. The AquaCrop model overestimated yield by 6.42–12.20%, while DSSAT-CROPGRO overestimated it by 5.74–12.52%. Considering specific temperature and water combinations, the TDWH showed the highest yield simulation accuracy (AquaCrop: $PE \leq 2.09\%$; DSSAT: $PE \leq 2.79\%$), whereas the THWD treatment showed the lowest accuracy (AquaCrop: $PE \leq 12.20\%$; DSSAT: $PE \leq 12.52\%$).

Table 7. Statistical indicators of tomato yield (Y), water consumption (ET), above-ground biomass (AB), and water use efficiency (WUE) simulated by AquaCrop and DSSAT-CROPGRO model under varying water and temperature conditions in 2024 and 2025.

Year	Model	Treatments	Y/(t·ha ^{−1})			AB/(t·ha ^{−1})			ET/(mm)			WUE/(kg·m ^{−3})		
			M	S	PE (%)	M	S	PE	M	S	PE	M	S	PE
2024	AquaCrop	TDWH	8.91	9.03	1.35	12.14	12.42	2.31	202.36	215.06	6.28	4.40	4.20	−4.64
		TDWD	8.44	8.66	2.61	10.64	10.67	0.28	195.56	207.26	5.98	4.32	4.18	−3.19
		THWH	7.32	7.79	6.42	11.62	11.71	0.77	292.75	281.98	−3.68	2.50	2.76	10.49
		THWD	6.69	7.34	9.72	10.79	10.7	−0.84	240.59	253.62	5.42	2.78	2.89	4.08
	DSSAT	TDWH	8.91	9.12	2.36	12.14	12.09	−0.41	202.36	210.59	4.07	4.40	4.33	−1.64
		TDWD	8.44	8.78	4.03	10.64	11.01	3.48	195.56	209.4	7.08	4.32	4.19	−2.85
		THWH	7.32	7.74	5.74	11.62	11.72	0.86	292.75	310.4	6.03	2.50	2.49	−0.27
		THWD	6.69	7.31	9.27	10.79	11.06	2.5	240.59	259.11	7.70	2.78	2.82	1.46
2025	AquaCrop	TDWH	8.61	8.79	2.09	13.42	13.53	0.82	191.56	202.62	5.77	4.49	4.34	−3.48
		TDWD	8.12	8.64	6.40	10.80	10.57	−2.13	183.17	199.07	8.68	4.43	4.34	−2.09
		THWH	7.18	7.87	9.61	12.82	12.52	−2.34	262.73	282.57	7.55	2.73	2.79	1.91
		THWD	6.15	6.90	12.20	10.01	9.8	−2.1	229.48	253.18	10.33	2.68	2.73	1.69
	DSSAT	TDWH	8.61	8.85	2.79	13.42	12.9	−3.87	191.56	200.68	4.76	4.49	4.41	−1.88
		TDWD	8.12	8.63	6.28	10.80	11.2	3.7	183.17	198.17	8.19	4.43	4.35	−1.76
		THWH	7.18	7.91	10.17	12.82	13.4	4.52	262.73	283.73	7.99	2.73	2.79	2.01
		THWD	6.15	6.92	12.52	10.01	10.72	7.09	229.48	253.4	10.42	2.68	2.73	1.90

M were the measured data; S were the simulated data; PE were the simulation error or percent deviation $(S - M)/M$, %

For AB, both models generally achieved high simulation accuracy across temperature and irrigation combinations. Under TD conditions, both models provided very good fits (AquaCrop: $-2.13 \leq PE \leq 2.31\%$; DSSAT: $-3.87 \leq PE \leq 3.70\%$). Under TH conditions, simulation accuracy slightly declined; with the largest deviation being 2.34% for AquaCrop and 7.09% for DSSAT-CROPGRO. This deviation may arise from the conservative setting of the water productivity coefficient in AquaCrop under complex environments, whereas DSSAT-CROPGRO may overestimate tomato growth under high-temperature conditions, indicating that the high-temperature inhibition functions for photosynthetic rate and assimilate accumulation still require localization and refinement under extreme greenhouse climates.

Regarding ET, both models performed satisfactorily under TDWD and TDWH (AquaCrop: $PE \leq 8.68\%$; DSSAT-CROPGRO: $PE \leq 8.19\%$). However, under high-temperature conditions, statistical analysis showed $PE \leq 10.33\%$ for AquaCrop, and $PE \leq 10.42\%$ for DSSAT-CROPGRO, indicating a significant decline in simulation accuracy. In most cases, ET was overestimated under high-temperature conditions. This suggests that the default crop transpiration parameters in the models may not be fully applicable to high-temperature greenhouse conditions, and further underscores the need to improve the dynamic representation of stomatal regulation and the localization of parameters under extreme climates.

Temperature and water combinations had significant effects on crop productivity. Regardless of temperature, yield and ET simulation accuracy were higher under full irrigation than under deficit irrigation. Notably, high temperature reduced the crop's productive potential. Compared with normal temperature, yields under high-temperature full and deficit irrigation treatments decreased by 17.0% and 22.0%, respectively. This reduction primarily results from combined heat and water stress limiting the preferential allocation of photosynthates to fruit, thereby constraining biomass accumulation.

5.4. Water and Temperature Control Strategies for Greenhouse Tomato

Figure 5 presents the predicted yield and WUE of greenhouse tomato under 20 treatment combinations (five temperature levels $\times$ four irrigation amount levels) based on the AquaCrop model. The highest yield occurred under the C8 treatment ($34^\circ\text{C} + 1.1E_{pan}$), while the lowest yield was observed under C17 ($40^\circ\text{C} + 0.5E_{pan}$). The highest WUE was found in C3 ($32^\circ\text{C} + 0.9E_{pan}$), whereas the lowest WUE occurred in C20 ($40^\circ\text{C} + 1.1E_{pan}$). Overall, both yield and WUE decreased with increasing temperature and decreasing irrigation. Regarding yield, under the same temperature level, it increased with higher irrigation amount. Under $0.9E_{pan}$ and $1.1E_{pan}$ treatments, yield exhibited a rise-then-fall trend with increasing temperature, peaking at 34°C ; however, under $0.5E_{pan}$, yield declined continuously with rising temperature. Notably, beyond 36°C , yield became less sensitive to changes in irrigation amount. For WUE, when temperatures were below 34°C , it increased with irrigation amount, but at temperatures above 34°C , further increasing irrigation amount actually reduced WUE. Under the same irrigation amount level, WUE consistently decreased with increasing temperature. It is noteworthy that at 38°C and 40°C , increasing irrigation amount from $0.7E_{pan}$ to $0.9E_{pan}$ slightly improved WUE, whereas further increasing to $1.1E_{pan}$ led to a decline.

These results indicate that 34°C represents a critical temperature threshold limiting tomato yield. Beyond this threshold, high temperature constrains carbon assimilation and biomass accumulation, causing fruit growth stagnation. Additionally, WUE decreases significantly above 34°C ; excessive irrigation under high-temperature and high vapor pressure deficit may induce partial stomatal closure to prevent water loss, thereby reducing stomatal conductance. The reduction in stomatal conductance limits transpiration, while the decline in photosynthetic rate exceeds the reduction in transpiration, leading to a marked decrease in WUE [43].

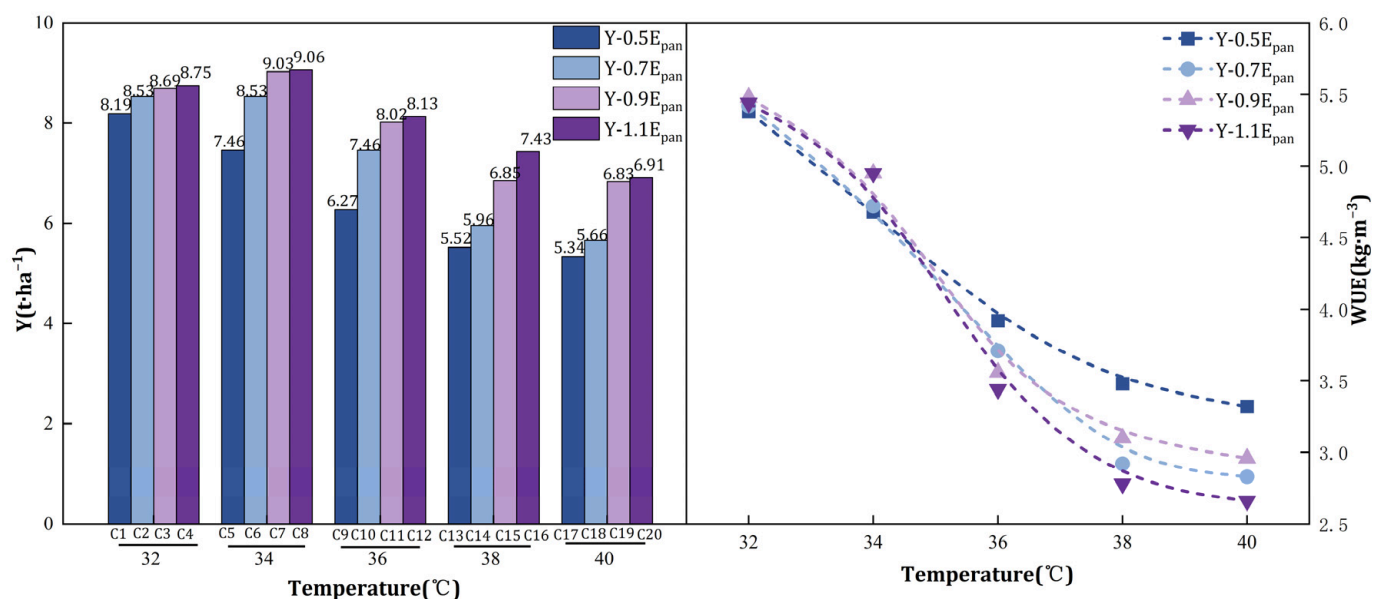


Figure 5. Scenario simulation diagram of crop yield and WUE under different combinations of water and temperature conditions.

6. Discussion

6.1. Performance of the Two Models in Simulating Crop Growth

Our study found that the AquaCrop and DSSAT-CROPGRO models can simulate CC of greenhouse tomato with acceptable accuracy. Previous studies on greenhouse tomato and field-grown potato also confirmed the reliability of these two models [15,44], and simulation accuracy tended to improve with increasing irrigation. Specifically, AquaCrop performed better under fully irrigated conditions, whereas DSSAT-CROPGRO showed relatively better performance under deficit irrigation. Notably, both models slightly underestimated CC during the early growth stage (by 5–10%), a phenomenon reported in previous studies [33,45,46]. For the DSSAT-CROPGRO model, this underestimation is attributable to the constraints of model parameter initialization: the allowable range for initial canopy parameters (0–50 cm² per plant) is smaller than the actual single-plant canopy at transplanting. For the AquaCrop model, the default setting assumes that plants experience water stress immediately after transplanting, whereas seedlings in the actual experiment were not subjected to water stress, leading to lower simulated CC values. In the later growth stages under TD conditions, simulated CC tended to be overestimated. This overestimation primarily results from the model not accounting for topping management in greenhouse tomato production (retaining only four fruit layers) and simulating continuous, unrestricted plant growth instead. Under TH conditions, overestimation by the DSSAT-CROPGRO model was even more pronounced. This is because the model evaluates temperature stress using a set of cardinal temperatures (T_{base} , T_{opt1} , T_{opt2} , T_{max}). If T_{max} is set too high or if the slope from optimal to maximum temperature is too gradual, the model interprets growth at 40 °C as merely slowed rather than representing physiological collapse. Consequently, the decline of CC in the model lags behind actual crop development [47]. Furthermore, if the model assumes that fruit development has ceased, carbon assimilates from photosynthesis are redistributed internally to stems and leaves, rather than contributing to fruit growth [48]. These observations highlight the necessity of reliable cultivar-specific parameters and mechanistic modules that account for stress responses to accurately simulate tomato growth under varying environmental conditions.

6.2. Performance of the Two Models in Simulating Soil Water Content

Our study demonstrated that the AquaCrop and DSSAT-CROPGRO models can generally simulate the dynamic changes in SWC in the tomato root zone (0–50 cm) under greenhouse conditions, consistent with previous studies on various crops [49]. However, both models tended to overestimate SWC during the seedling stage after transplanting. This deviation is mainly attributable to insufficient accuracy in simulating soil surface evaporation. During the seedling stage, when the canopy is not yet fully developed, soil water loss is primarily driven by soil evaporation. Existing models typically estimate potential evaporation based on meteorological data, which may underestimate surface soil water exchange under the low-wind, high-humidity microclimate typical of greenhouses [50]. Additionally, the models adopt conservative assumptions regarding the initial root water uptake zone, resulting in calculated root-zone water consumption lower than actual values, thereby producing higher simulated soil water content [51]. Notably, under normal temperature and adequate water conditions TDWH, both models exhibited satisfactory simulation accuracy, confirming their applicability in favorable environments. In contrast, under combined high-temperature and water deficit conditions THWD, model performance declined, with some cases showing model failure. Mechanistically, this highlights structural limitations in the root water uptake modules under extreme conditions. Current models often assume that root water uptake is primarily controlled by soil water potential, with a direct relationship between soil water potential and uptake efficiency. While this assumption aligns with crop growth mechanisms under TD conditions, it fails under high-temperature stress, where plants regulate transpiration non-linearly through stomatal adjustments and complex physiological feedbacks that the models cannot capture. Moreover, combined temperature and water stress may alter root distribution, with plants typically developing deeper roots to cope with drought, whereas the models assume a static root distribution, preventing accurate representation of soil water depletion under extreme conditions [52,53]. Therefore, improving soil evaporation modules and root water uptake functions to account for extreme greenhouse environments is critical for future optimization of the AquaCrop and DSSAT-CROPGRO models.

6.3. Performance of the Two Models in Simulating Yield, ET, AB and WUE

Although the AquaCrop and DSSAT-CROPGRO models generally provide acceptable accuracy in simulating yield under different environments, discrepancies between simulated and potential yields persist. Cheng et al. reported that AquaCrop underestimated yield by 8.2–40.4%, largely attributable to insufficient representation of yield formation processes during crop establishment and flowering [33]. Multiple studies have indicated that inadequate targeted parameter calibration and the absence of specific stress-response modules are key sources of error [13,54]. In particular, deficiencies in phenology simulation are prominent: existing models often simplify phenological development as a function of temperature, neglecting the significant regulatory effects of water and nitrogen deficits on flowering and maturity [55,56], which prevents accurate representation of phenological differences under varying water treatments. In this study, we observed that simulation accuracy under combined high-temperature and water deficit conditions THWD was significantly lower than under normal temperature and adequate water TDWH. From a temperature perspective, yield reductions under high temperature primarily resulted from decreased photosynthetic rates and reduced biomass accumulation. Current process-based models, however, oversimplify these nonlinear physiological responses under extreme conditions. For instance, AquaCrop adjusts only the K_5 coefficient to modify HI_0 in response to high-temperature stress, which is overly simplistic, while DSSAT-CROPGRO applies smoothed thermal response curves that overestimate crop photosynthetic resilience under extreme heat [57]. From a water perspective, deficit irrigation markedly reduced leaf area

and above-ground biomass accumulation, while root dry weight decreased significantly, suppressing overall plant growth. Consequently, the root-to-shoot ratio increased, with more biomass allocated to roots at the expense of yield formation. Both models failed to capture these shifts, contributing to the observed discrepancies. Moreover, *ET* and *WUE* are key indicators in water-driven modeling; however, both AquaCrop and DSSAT-CROPGRO tended to overestimate *ET* to varying degrees, with simulation errors decreasing as temperature and irrigation increased, consistent with previous studies [58]. These discrepancies are largely attributable to the core *ET* modules of AquaCrop and DSSAT-CROPGRO, which are derived from energy balance equations for open-field conditions. The embedded aerodynamic resistance parameters cannot adequately adapt to the low-wind, high-humidity environments typical of greenhouses, leading to systematic biases in simulation. These findings underscore the need for targeted optimization of water consumption modules to improve the accuracy of key crop indicators. Critically, such improvements should specifically address simulation biases under high-temperature conditions, thereby compensating for current model limitations under extreme temperature scenarios.

6.4. AquaCrop Model Scenario Simulation

Our study used scenario-based simulations to systematically analyze the effects of different temperature levels (32–40 °C) and irrigation amount gradients (0.5–1.1 E_{pan}) on crop yield and *WUE*. We identified a critical temperature threshold at 34 °C for both yield and *WUE* responses: below 34 °C, yield reached its maximum under 1.1 E_{pan} , whereas above 34 °C, yield and *WUE* decreased across all irrigation treatments. This finding was consistent with previous studies [56,59], which reported negative impacts of heat stress on tomato. At 35 °C, both flowering and fruit set are inhibited, and at temperatures exceeding 40 °C, severe flower and fruit drop occurs, with prolonged heat stress resulting in substantial losses of reproductive organs.

Notably, the regulatory effect of irrigation amount on yield and *WUE* was found to be temperature-dependent. At temperatures ≤ 34 °C, increasing irrigation amount from 0.5 E_{pan} to 0.9 E_{pan} significantly improved both yield and *WUE*, whereas further increasing to 1.1 E_{pan} produced only marginal gains (maximum increase of 0.74%), consistent with [59]. This is likely due to excessive soil water under full irrigation restricting root growth, reducing the root-to-shoot ratio, and limiting root biomass allocation, thereby impairing nutrient uptake. Under high-temperature stress, even 1.1 E_{pan} irrigation could not prevent the decline in yield and *WUE*; instead, 0.7 E_{pan} and 0.9 E_{pan} showed comparatively better performance. This indicates that when temperature exceeds the crop's tolerance limit, damage to the photosynthetic system becomes the dominant factor limiting productivity, and supplemental water can only partially mitigate plant dehydration without reversing declines in photosynthetic efficiency. Based on these results, we suggest that when temperatures are ≤ 34 °C, an irrigation level of 0.9 E_{pan} best balances yield and *WUE*. Under high-temperature stress (≥ 36 °C), maintaining 0.9 E_{pan} is recommended to balance yield stability and water resource efficiency, thereby avoiding unnecessary resource waste.

The practical feasibility and economics of these strategies also merit consideration. For temperature, our experiment showed that the target level is attainable in a naturally ventilated greenhouse: without intervention the indoor temperature could reach about 45 °C in summer, whereas forced ventilation lowered it to around 34 °C, indicating that temperature control at the recommended level is operationally feasible through ventilation rather than costly active cooling. Under more extreme heat, or in greenhouses with limited ventilation capacity, maintaining this level may require additional inputs; in such cases a target below 36 °C provides a more realistic balance between performance and feasibility. For irrigation, applying more than the full replacement level (1.1 E_{pan}) did not increase

yield appreciably and gave the lowest WUE, so it is not economically justified, whereas $0.7\text{--}0.9E_{pan}$ offers a more practical balance between yield and water-use efficiency. Overall, a distinction should be drawn between the theoretical optimum identified by the scenario analysis (maximum yield near $34\text{ }^{\circ}\text{C}$ with high irrigation) and the practical recommendation for production (below $36\text{ }^{\circ}\text{C}$ with $0.7\text{--}0.9E_{pan}$), the latter accounting for operational feasibility and economic considerations.

6.5. Mechanistic Interpretation of Model Performance Under High-Temperature Stress

Our study found that AquaCrop was generally more robust than DSSAT-CROPGRO under high-temperature conditions across most indicators. This is consistent with the studies by [15,37]. It should be noted that this advantage does not indicate that one model is absolutely superior to the other; rather, it depends on whether each model's structure is consistent with the actual response of the crop to combined heat and water stress.

From the perspective of crop physiology, Schauburger et al. [60] reported that when temperature exceeds about $30\text{ }^{\circ}\text{C}$, yield loss is to a large extent mediated through water stress and can therefore be partly alleviated by irrigation. This is precisely the pathway that a water-driven model represents directly. In terms of model structure, AquaCrop first calculates crop transpiration from the soil–water balance and then converts it into biomass through normalized water productivity (WP); because WP is normalized by the atmospheric evaporative demand (ET_0), the relationship between biomass and transpiration remains structurally stable across different environments. Its stress responses are expressed through a set of soil–water-based coefficients ($K_{s,exp,w}$, $K_{s,sto}$, $K_{s,sen}$) that mainly affect canopy expansion, stomatal conductance, and senescence. Under greenhouse high temperature combined with water deficit, this water-centered structure therefore captures the key pathway that governs yield formation. By contrast, DSSAT-CROPGRO is mainly radiation- and carbon-driven: it first calculates canopy photosynthesis and then partitions assimilates, so photosynthesis is the basis of the entire simulation. However, photosynthesis is the process most difficult to simulate accurately under high temperature, which means that the most fundamental component of the model is also the most error-prone. The key departure lies in how this core represents temperature. CROPGRO evaluates heat stress through smoothed cardinal-temperature response curves, which, like the Arrhenius-type functions used in most large-scale process models, treat the decline of assimilation under high temperature as gradual and reversible. In reality, however, once a critical threshold is exceeded, photosynthetic losses become abrupt but irreversible as enzymes are denatured and membrane integrity is impaired. This discrepancy causes the simulated decline in canopy cover to lag behind the actual crop response, and DSSAT consequently overestimates biomass and yield. More broadly, most process-based models were not originally designed to reproduce short-duration temperature extremes, and their threshold-insensitive, daily-mean-temperature responses are a widely recognized limitation [61].

These structural differences also explain why the two models diverge unevenly among indicators. For canopy cover, both models were calibrated directly against observations and performed similarly; the difference between the water-driven and carbon-driven models emerges mainly in biomass and yield. It should be noted that AquaCrop's advantage under high temperature is structural rather than absolute: although it operates along the correct water pathway, it still summarizes environmental effects on the crop through simplified stress factors, at the expense of mechanistic detail, which is one of its limitations. The richer carbon- and temperature-based mechanisms of DSSAT-CROPGRO are more detailed, but they introduce limitations when these functions are not accurately specified. This further confirms the need, noted in Section 6.3, to localize and refine the high-temperature response functions of process-based models for extreme greenhouse climates.

6.6. Future Development of AquaCrop and DSSAT Models

The analysis above indicates that the primary sources of error in simulating high-temperature conditions with the AquaCrop and DSSAT-CROPGRO models lie in two aspects. First, parameter uncertainty: interactions between high temperature and water stress elicit nonlinear physiological responses in crops, which are difficult to fully optimize using conventional trial-and-error or statistical approaches, thus limiting model accuracy. Second, inherent structural limitations: while existing models adequately capture responses to single stress factors, their mechanistic representation under combined heat and water stress remains insufficient.

To overcome the limitations in parameter calibration, intelligent optimization algorithms have been widely applied to parameter estimation under various stress conditions due to their efficiency in multi-objective global optimization. Nevertheless, their application under scenarios of combined temperature and water stress remains limited. Furthermore, although machine learning has been extensively used to predict crop yields under future climate scenarios, it predominantly constructs linear or nonlinear correlations between meteorological variables and yield, functioning as a “black-box” approach with limited capacity to reflect intrinsic crop growth processes. In contrast, mechanistic crop models systematically capture the coupling between crops and the environment but are constrained by limited adaptability in specific modules. Machine learning, while lacking mechanistic interpretability, offers strong data-fitting capacity and excels at modeling complex nonlinear relationships. Therefore, integrating the complementary strengths of mechanistic modeling and machine learning may provide a promising strategy for enhancing crop simulation performance under extreme climate conditions.

6.7. Limitations

Several limitations of this study should be acknowledged. First, temperature treatments were not replicated at the greenhouse level: in each year, each temperature level was assigned to a single greenhouse. To reduce the risk that the temperature effect would be confounded with any fixed characteristic of a specific greenhouse, the two temperature treatments were rotated between the greenhouses across the two years (greenhouse 1 was the high-temperature unit in 2024 and greenhouse 2 in 2025), and no temperature or water treatments were imposed during the seedling stage. This rotation reduces the risk that the reported temperature effects are confounded with fixed differences between the two greenhouses, although it does not provide independent within-year replication of the temperature treatment.

Second, the work was conducted at a single location (Zhengzhou), in a single greenhouse type (a semi-automatic, naturally ventilated solar greenhouse), and with a single tomato cultivar (“Jingfan 404”). The model parameters were calibrated and validated at the same experimental site; because the parameters of process-based crop models are site- and cultivar-specific, the calibrated parameters and the management strategies derived here apply to the local conditions studied, and should be re-calibrated before being applied to other regions or cultivars.

Third, the modeling approach carries inherent uncertainty: the AquaCrop and DSSAT-CROPGRO models showed reduced accuracy for soil water content and ET under high-temperature conditions, and the XGBoost-based ET_0 estimation used in the scenario analysis is subject to prediction error. These uncertainties propagate into the scenario outputs, which should therefore be interpreted as indicative trends rather than precise predictions. A formal uncertainty analysis (e.g., ensemble or Monte Carlo approaches) is a valuable direction for future work.

7. Conclusions

In this study, the AquaCrop and DSSAT-CROPGRO models were applied for parameter localization and validation to simulate canopy cover, soil water content, yield,

above-ground biomass, water consumption, and water use efficiency under varying temperature and water treatments during the 2024 and 2025 tomato growing seasons. The results indicate that AquaCrop performed well in simulating canopy cover and yield under normal temperature conditions, particularly under adequate irrigation. However, its performance in simulating soil water content and water consumption was relatively poor, and the model showed reduced accuracy under high-temperature and low-water treatments. For the DSSAT-CROPGRO model, due to its limited representation of temperature and water stress, simulation accuracy for canopy cover, soil water content, yield, and water consumption was lower than that of AquaCrop under both normal and high-temperature conditions, with close agreement with observations only under normal temperature and fully irrigated treatments. Therefore, for greenhouse tomato simulations involving high-temperature scenarios, AquaCrop is recommended as a balanced modeling choice, considering both data requirements and accuracy.

Scenario simulations further showed that irrigation levels of $0.7E_{pan}$ and $0.9E_{pan}$ could achieve an optimal balance between biomass production and water use efficiency. In contrast, $0.5E_{pan}$, although yielding relatively high water use efficiency, resulted in a significant reduction in yield, while $1.1E_{pan}$ did not substantially increase yield and exhibited the lowest water use efficiency. Considering both yield and water use efficiency, maintaining irrigation amount at $0.7\text{--}0.9E_{pan}$ and controlling temperature below $36\text{ }^{\circ}\text{C}$ is recommended to achieve optimal tomato production performance.

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