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CPSM: A Dynamic Simulation Model for Cucumber Productivity in Solar Greenhouse Based on the Principle of Effective Accumulated Temperature

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Abstract: The Cucumber Productivity Simulation Model (CPSM) was developed to precisely predict the dynamic process of cucumber productivity in a solar greenhouse. This research conducted a variety of sowing experiments and collected data on cucumber productivity and meteorological conditions from 2013 to 2015 and 2018 to 2020. Employing the principles of least squares, the relationship between cucumber productivity indicators and effective accumulated temperature (EAT) was fitted, determining key crop parameters and constructing the CPSM. Validation of the model was conducted using independent experimental data, evaluating its simulation accuracy. The results indicate that (1) CPSM can dynamically and meticulously simulate the formation process of different productivity indicators in cucumber. Normalized root mean square errors (NRMSE) ranged from 0.44% to 19.64%, and mean relative errors (MRE) ranged from 0.31% to 17.23% across different productivity indicator models. The models for organ water content, maximum root length, specific leaf area, and organ fresh weight distribution index demonstrated high simulation accuracy, while others showed relatively high accuracy. (2) Simulation accuracy varied with indicators and varieties. 19 indicators (34.55%) exhibited high simulation accuracy and 30 indicators (54.55%) showed relatively high accuracy. The JY35 variety ($10.44 \pm 8.49\%$) outperformed the JS206 variety ($13.44 \pm 8.50\%$) in terms of simulation accuracy. The JY35 variety had 39 superior productivity indicators (70.91%) while the JS206 variety had sixteen (29.09%). CPSM utilizes easily accessible temperature data as its input, allowing for precise and detailed simulation of productivity indicators for cucumber production in solar greenhouses. This research lays a theoretical foundation and provides technical support for guiding intelligent production management, efficient utilization of agricultural resources, and climate change productivity assessment in solar greenhouse cucumber production.

Keywords: accumulated temperature method; accurate dynamic simulation model; model statistical evaluation; productivity and meteorology; variety and indicator differences



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1. Introduction

Crop models, which are driven by environmental factors such as temperature, light, soil, and water, are used to quantitatively describe and predict crop productivity and quality formation using computer technology and physical–mathematical methods [1,2]. These models provide a mechanism for understanding the growth and development processes

of crops and have been applied in various areas, including crop productivity forecasting at specific sites and regions [3], quantifying the effects of climate change [4], and decision-making in digital design and field management [5]. However, most of these studies have focused on field crops [6–8], and there is an urgent need to develop and apply production models for horticultural crops grown in controlled environments.

The accumulating temperature (AT) theory proposed by McMaster et al. states that the accumulated temperature required for crop development is relatively constant [9]. This theory offers several advantages, including the simplicity of input data, few measurable model parameters, high accuracy, and strong extrapolation ability. Although scholars have made improvements to crop modeling algorithms, progressing from simple temperature models to more complex integrated models such as light–temperature models and light–thermal–water–fertilizer–soil models [10–12], the accumulating temperature model remains a significant component of crop productivity models. Moreover, the algorithms for accumulating temperature models have evolved from simple summation of daily average temperatures to incorporating lower temperature thresholds for active accumulating temperature (AAT) and effective accumulating temperature (EAT) [12,13]. Currently, the effective accumulating temperature model has been applied in predicting the productivity of grain crops such as wheat [14,15], maize [16,17], and rice [18,19], horticultural crops like apples [20], cherries [21], citrus [22], walnuts [23], as well as ornamental crops such as tulips [13]. These applications have demonstrated high simulation accuracy, indicating the strong extrapolation ability of the effective accumulating temperature model.

Regarding the prediction of productivity in vegetable horticulture, scholars have developed general vegetable horticulture models such as HORTISIM [24] and SIMULSERRE [25], which can quantitatively simulate the processes of developmental stages and phenology, organ generation and completion, photosynthetic production and substance accumulation, assimilate distribution, and yield-quality formation. However, due to the diverse types of vegetable varieties and significant differences in growth characteristics and cultivation management methods, the accuracy of such general models is still in need of improvement. Consequently, researchers have further developed targeted greenhouse tomato production simulation models such as TOMGRO [26] and TOMSIM [27] and have conducted studies on model uncertainty analysis [28], model coupling prediction analysis [29], and parameter sensitivity analysis [30] to enhance the accuracy and universality of the models. However, these models still face challenges such as complex and difficult-to-obtain parameters, requiring a large amount of experimental data for parameter localization, which results in such models having poor extrapolation capabilities. Currently, there are few productivity models available for greenhouse cucumber, which has high production and economic benefits. Therefore, it is worth exploring the combination of dynamic simulation of different cucumber varieties' productivity using an effective growing degree day model algorithm.

Based on the conducted variety sowing date experiment and collection of cucumber productivity and meteorological data, this study successfully established the Cucumber Productivity Simulation Model (CPSM) based on the effective accumulated temperature (EAT). By fitting the relationship between productivity indicators and EAT, the model's key crop parameters were determined. Additionally, the model was validated using independent experimental data, and its simulation accuracy was evaluated. The CPSM was developed to precisely predict the dynamic process of cucumber productivity in a solar greenhouse and provide a theoretical basis and technical support for guiding smart production management, efficient utilization of agricultural resources, and productivity assessment in the face of climate change in greenhouse cucumber production.

2. Materials and Methods

2.1. Experimental Design

The experiment was conducted in a solar greenhouse in the agricultural technology innovation base in Wuqing District, Tianjin, China (39°25'48" N, 116°58'12" E; the altitude is 8 m) from 2013 to 2015 and from 2018 to 2020. The tested cultivar in the years 2013–2015

was Jinyou 35 (JY 35), while in the years 2018–2020, it was Jinsheng 206 (JS 206). JY35 variety leaves are medium sized and are mainly used for main vine melons. They have a strong ability to produce female flowers, with a fruit-setting rate of less than 10%. They have good early maturity and the length of their waist gourd is between 32 and 34 cm, with a misshapen fruit rate of less than 5%. They are suitable for winter cultivation in sunlight greenhouses and early spring cultivation. JS206 variety leaves are also medium sized. They have a stable early yield and outstanding yield in the middle and later stages. The length of their waist gourd is 34 cm. They are suitable for early spring and summer protected cultivation. In order to improve the annual productivity level of cucumber in a solar greenhouse, the planting was divided into two crops each year—the spring crop and the autumn–winter crop, totaling 7 crops. The experiment was conducted in stages, with each crop divided into 3 transplanting periods, totaling 21 transplanting periods. Early sowing was defined as that which occurred 15 days earlier than the local conventional transplanting date, middle sowing was defined as the local conventional transplanting date (early February for the spring crop and early September for the autumn–winter crop), and late sowing was defined as 15 days later than the local conventional transplanting date. Each transplanting period had 3 replicates, and a randomized complete block design was used. The planting row spacing was 0.67 m, the plant spacing was 0.42 m, and the planting density was $3.555 \text{ plants} \cdot \text{m}^{-2}$. The solar greenhouse was constructed with masonry walls. The rear wall of the greenhouse had a height of 3.7 m and a thickness of 0.5 m. The side wall had a thickness of 0.5 m, while the ridge height was 5.3 m. The rear roof had an elevation angle of 44.0° , while the front roof had an angle of 32.0° . The span of the roof was 10.0 m, its length was 65.0 m, and it occupied a total area of 650.0 m^2 . The soil texture of the experimental site was heavy clay. The total nitrogen content in the cultivation layer (from 0 to 20 cm) was $2.76 \text{ g} \cdot \text{kg}^{-1}$, the hydrolyzed nitrogen content was $227.8 \text{ mg} \cdot \text{kg}^{-1}$, the available phosphorus content was $299.2 \text{ mg} \cdot \text{kg}^{-1}$, the available potassium content was $648.0 \text{ mg} \cdot \text{kg}^{-1}$, the organic matter content was $43.0 \text{ g} \cdot \text{kg}^{-1}$, the pH was 7.61, and the cation exchange capacity was $73.44 \text{ cmol} \cdot \text{kg}^{-1}$.

2.2. Data Sources

2.2.1. Crop Data

This study divided the growth and development process of cucumbers into 7 key developmental stages: transplanting date (T), stretch tendril period (ST), initial flowering period (IF), fruiting period (F), early harvest period (EH), harvest period (H), and uprooting period (U). The T period begins when the third true leaf emerges and the fourth true leaf appears, which is commonly known as three leaves and one heart. The ST period begins when the fourth true leaf unfolds and the fifth true leaf emerges, known as four leaves and one heart. During this period, the internode length increases and tendrils start to appear in the leaf axils, changing from an upright to a trailing growth habit. The plant transitions from slow growth to rapid growth, marking the end of the seedling stage. The IF period is identified by the emergence of the first female flower. In cultivation management, only flowers above the sixth leaf are retained. The F period is reached when the root squash changes from yellow-green to deep-green, indicating that the squash has settled. After the flowers wither, 2–3 cm immature fruits begin to grow. The EH period is when the root squash reaches maturity, meeting the harvest standards, at which point the fruit length is about 30 cm, and the elongation and thickening process is basically completed, resulting in a crisp and fragrant taste. The H period includes the harvest of waist squash, top squash, back squash, and lateral vine squash when they meet the harvest standards. The U period is characterized by yellowing stems and leaves, slow maturation of the fruit, and overall plant aging, which is associated with seasonal production capacity, stubble combination and utilization efficiency of photothermal resources. The recording technique used during the developmental period relied on the morphological traits of more than 50% of the experimental population that had reached this stage of development [31]. Cucumber was an infinitely growing horticultural plant that underwent multiple pruning and harvesting

processes during production [12,31]. This study employed a single vine pruning method to promptly prune the functional branches and leaves of pests and illnesses that had diminished photosynthetic capability and excessive nutrient consumption. Typically, in the process of production, plants maintained a range of 13 to 15 fully developed leaves. When establishing the CPSM, only the productivity status of cucumber after pruning management was taken into account. The individual plant yield was calculated based on real-time fruit harvest, without factoring in the productivity status of cucumber after pruning management. The sampling frequency for this experiment was 10 days each. Three representative plants were selected for each treatment during each sampling period. The mean values were ultimately calculated to determine various growth indicators.

Organ Dry and Fresh Weight

Organ fresh weight referred to each the weight of each organ measured on an electronic balance within 3 h after sampling, g. The fresh weight of root, tendril, flower, main stem, petiole, stem, carpopodium, and leaf was recorded as W_{f_r} , W_{f_t} , W_{f_f} , W_{f_m} , W_{f_p} , W_{f_s} , W_{f_c} and W_{f_l} . Organ dry weight referred to each organ divided into kraft paper bags and placed in an oven. First, it was sterilized at 105 °C for 0.5 h, then dried at 80 °C to a constant weight, and finally the weight of each organ was determined using an electronic balance, which relayed the weight in g. The dry weight of root, tendril, flower, main stem, petiole, stem, carpopodium, and leaf was recorded as W_{d_r} , W_{d_t} , W_{d_f} , W_{d_m} , W_{d_p} , W_{d_s} , W_{d_c} and W_{d_l} . The weight of stem was the sum of the weight of the main stem and petiole (Formula (1)). The plant overground weight was the sum of the weights of the tendril, flower, main stem, petiole, carpopodium, and leaf (Formula (2)), and the plant overground fresh weight was recorded as W_{f_o} ; the plant overground dry weight was recorded as W_{d_o} . The weight of whole plant was the sum of the weight of the root, tendril, flower, main stem, petiole, carpopodium, and leaf (Formula (3)), and the fresh weight of whole plant was recorded as W_{f_w} , the dry weight of whole plant was recorded as W_{d_w} . The yield referred to the cumulative weight of harvested fruit, which was divided into fresh weight yield (Y_{f_f}) and dry weight yield (Y_{d_f}).

$$W_s = W_m + W_p \quad (1)$$

$$W_o = W_t + W_f + W_m + W_p + W_c + W_l \quad (2)$$

$$W_w = W_r + W_o \quad (3)$$

where W_s was the dry and fresh weight of the stem in g. W_m was the dry and fresh weight of the main stem in g. W_p was the dry and fresh weight of the petiole in g. W_o was the dry and fresh weight of plant overground in g. W_t was the dry and fresh weight of the tendril in g. W_f was the dry and fresh weight of the flower in g. W_c was the dry and fresh weight of the stem in g. W_l was the dry and fresh weight of the leaf in g. W_r was the dry and fresh weight of the root in g.

Organ Dry and Fresh Weight Distribution Index

The organ dry and fresh weight distribution index referred to the ratio of the dry and fresh matter weight of each organ to the dry and fresh weight of the whole plant (Formula (4)). The fresh weight distribution index for the root, tendril, flower, main stem, petiole, stem, carpopodium, and leaf were denoted as DI_{f_r} , DI_{f_t} , DI_{f_f} , DI_{f_m} , DI_{f_p} , DI_{f_s} , DI_{f_c} and DI_{f_l} . The dry weight distribution index for the root, tendril, flower, main stem, petiole, stem, carpopodium, and leaf were denoted as DI_{d_r} , DI_{d_t} , DI_{d_f} , DI_{d_m} , DI_{d_p} , DI_{d_s} , DI_{d_c} and DI_{d_l} . The dry and fresh weight distribution index of the stem was the sum of the dry and fresh weight distribution index of the main stem and petiole (Formula (5)). Therefore, the sum of the dry and fresh weight distribution index of the root, tendril, flower, petiole, carpopodium, and leaf was equal to the sum of the dry and fresh weight distribution indices of the root, tendril, flower, stem, carpopodium, and leaf, which were 100% (Formula (6)).

$$DI_j = W_j / W_w * 100\% \quad (j = 1, 2, \dots, 8) \quad (4)$$

$$DI_s = DI_m + DI_p \quad (5)$$

$$DI_r + DI_t + DI_f + DI_s + DI_c + DI_l = 100\% \quad (6)$$

where $j = 1, 2, \dots, 8$, respectively, represented the root, tendril, flower, main stem, petiole, stem, carpopodium, and leaf. DI_j represented the dry and fresh weight distribution index of organ j , %. W_j represented the weight of fresh and dry substances in organ j in g. W_w represented the dry and fresh weight of the whole plant in g. DI_s was the dry and fresh weight distribution index of organ stems, %. DI_m was the dry and fresh weight distribution index of the main stem, %. DI_p was the dry and fresh weight distribution index of the petiole, %. DI_r was the dry and fresh weight distribution index of the root, %. DI_t was the dry and fresh weight distribution index of the tendril, %. DI_f was the dry and fresh weight distribution index of the flower, %. DI_c was the distribution index of the dry and fresh weight of the stem, %. DI_l was the dry and fresh weight distribution index of leaf, %.

Organ Water Content

Organ water content referred to the ratio of organ water weight to organ fresh weight (Formula (7)). The relative water content of the root, tendril, flower, main stem, petiole, stem, carpopodium, and leaf was denoted as WC_r , WC_t , WC_f , WC_m , WC_p , WC_s , WC_c and WC_l .

$$WC_j = (W_{f-j} - W_{d-j}) / W_{f-j} * 100\% \quad (j = 1, 2, \dots, 8) \quad (7)$$

where WC_j was the relative water content of organ j , %. W_{f-j} was the fresh weight of organ j in g. W_{d-j} was the dry weight of organ j in g.

Stem Volume

This study only considered the volume of stem and assumed that the organ stems were cylindrical. Therefore, the stem volume could be calculated using the stem length and diameter (Formula (8)). The volume of the main stem, petiole, and stem was denoted as V_m , V_p , and V_s .

$$V_i = \pi * (D_i/10)^2 * L_i \quad (i = 1, 2, 3) \quad (8)$$

where $i = 1, 2$, and 3 , respectively, represented the main stem, petiole, and stem. V_i was the volume of organ i in cm^3 . D_i is the diameter of organ i in mm. L_i was the length of organ i in cm.

The root to shoot ratio was the ratio of the dry and fresh weight between the plant underground and overground (Formula (9)) [32], which was divided into fresh weight root to shoot ratio (RS_f) and dry weight root to shoot ratio (RS_d). The plant height was the distance between the top of root and the top of the plant [33], denoted as H , in cm. The maximum root length was the distance from the bottom of root to the bottom of the stem [33], denoted as L_r , in cm. Leaf rea was observed using the coordinate paper method [33], denoted as LA . The leaves were placed flat on the coordinate paper and calculated each leaf area in a numerical grid manner. If the leaf edge exceeded half a grid, it was calculated as 1. If it was less than half a grid, it was calculated as 0. The leaf area index was calculated as the product of the leaf area and planting density (Formula (10)) [34], denoted as LAI . The specific leaf area was the ratio of the leaf area to leaf dry weight (Formula (11)) [35], denoted as SLA .

$$RS = W_r / W_o \quad (9)$$

$$LAI = LA * d / 10^4 \quad (10)$$

$$SLA = LA / W_{d-l} \quad (11)$$

where RS was the ratio of dry and fresh root to shoot of the plant in $\text{g} \cdot \text{g}^{-1}$. LAI was the leaf area index in $\text{m}^2 \cdot \text{m}^{-2}$. LA was the leaf area per plant in cm^2 , d was the planting density ($3.555 \text{ plant} \cdot \text{m}^{-2}$) and 10^4 was the unit conversion coefficient between cm^2 and m^2 . SLA was the specific leaf area in $\text{cm}^2 \cdot \text{g}^{-1}$.

2.2.2. Meteorological Data

The greenhouse microclimate was monitored using a microclimate observation instrument called CAWS2000 (Beijing Huayun Shangdong Technology Co., Ltd., Beijing, China). This instrument automatically collected meteorological data, including air temperature, humidity, CO_2 concentration, and total solar radiation, at 10 min intervals. The encrypted auxiliary observation employed a small climate observation instrument called Hobo (ONSET Technology Co., Ltd., Cape Cod, MA, USA), which autonomously logged meteorological data, including the air temperature, humidity, and total solar radiation, at 5 min intervals.

This study made the assumption that there is a direct relationship between the rate of growth and development of cucumbers and temperature. The effective accumulated temperature (EAT) was determined by calculating the difference between the average temperature and the biological lower limit temperature (Formula (12)) [12].

$$EAT = \begin{cases} \sum(T_{\text{ave}} - T_b), & T_{\text{ave}} \geq T_b \\ 0, & T_{\text{ave}} < T_b \end{cases} \quad (12)$$

where T_{ave} was the daily average temperature in $^{\circ}\text{C}$. T_b was the biological lower limit temperature, $^{\circ}\text{C}$, which was related to the developmental stage, with the T to ST stage valued at 13°C , ST to IF valued at 14°C , and IF to U valued at 16°C [12].

2.3. Validation Statistical Indicators

This study established a model based on ET and LT experimental data. The validated model based on independent MT experiment data. Microsoft Excel 2013 was utilized for data processing and visualization. The statistical indicators for the model mainly include the average ($\bar{X}$), standard deviation (SD), linear regression coefficients (α), linear regression constant (β), determination coefficient (R^2), root mean square error (RMSE) (Formula (13)) [31], normalized root mean square error (NRMSE) (Formula (14)) [31], mean absolute error (MAE) (Formula (15)) [36], mean relative error (MRE) (Formula (16)) [36], and compliance index (D) (Formula (17)) [31].

$$\text{RMSE} = \sqrt{\frac{\sum(X_{\text{obs}} - X_{\text{sim}})^2}{N}} \quad (13)$$

$$\text{NRMSE} = \frac{\text{RMSE}}{X_{\text{obs}}} * 100\% \quad (14)$$

$$\text{MAE} = \frac{\sum|X_{\text{obs}} - X_{\text{sim}}|}{N} \quad (15)$$

$$\text{MRE} = \frac{\sum|X_{\text{obs}} - X_{\text{sim}}|}{X_{\text{obs}} * N} * 100\% \quad (16)$$

$$D = 1 - \frac{\sum(X_{\text{obs}} - X_{\text{sim}})^2}{\sum[|X_{\text{obs}} - X_{\text{obs}}| + |X_{\text{sim}} - X_{\text{obs}}|]^2} \quad (17)$$

where X_{obs} was the experimental observation. X_{sim} was the experimental simulation. $\bar{X}_{\text{obs}}$ was the average of experimental observations. N was the number of samples. This study comprehensively evaluated the accuracy of the model by calculating the average of NRMSE and MRE (A_{NM}). If A_{NM} was less than 10%, this illustrated that the simulation accuracy was extremely high. If $10\% < A_{NM} < 20\%$, this illustrated that the simulation accuracy was high. If $20\% < A_{NM} < 30\%$, this illustrated that the simulation accuracy was general. If

A_{NM} was greater than 30%, this illustrated that the simulation accuracy was poor. The advantage productivity indicator was defined as a productivity indicator where the mean RMSE, NRMSE, MAE, and MRE statistics proportion was less than 50%, otherwise, it was considered a disadvantage productivity indicator.

2.4. Establishing Model

The present study utilizes early sowing and late sowing data for model construction. By applying the principle of least squares, the relationship between cucumber productivity index and effective accumulated temperature (EAT) is fitted. The fitting forms mainly include mean type (Formula (18)), linear type (Formula (19)), logarithmic type (Formula (20)), and logistic type (Formula (21)), resulting in the CPSM's initial parameters. The model's final parameters are obtained through parameter tuning (Table 1).

$$I_{mean} = a \quad (18)$$

$$I_{linear} = a * EAT + b \quad (19)$$

$$I_{logarithmic} = a * \ln(EAT) + b \quad (20)$$

$$I_{logistic} = c / (1 + e^{a*EAT+b}) \quad (21)$$

where I_{mean} is the mean type indicator that does not change with the change in EAT, including DI_{f_t} , DI_{d_t} , WC_r , WC_t , WC_f , WC_p , WC_c , WC_l and SLA of JY35 and JS206 variety, and W_{f_t} , W_{f_f} , W_{f_p} , W_{f_l} , W_{d_t} , W_{d_f} , W_{d_p} , W_{d_l} , DI_{f_r} and DI_{d_r} of JY35 variety. I_{linear} is the linear type indicator that shows a linear trend with the increase in EAT, including DI_{f_m} , DI_{f_p} , DI_{f_s} , DI_{f_l} , DI_{d_m} , DI_{d_p} , DI_{d_s} and DI_{d_l} of JY35 and JS206 variety, where DI_{f_p} , DI_{f_l} , DI_{d_p} and DI_{d_l} show a linear decrease, and other productivity indicators show a linear increase. $I_{logarithmic}$ is a logarithmic type indicator that shows a logarithmic trend with the increase in EAT, including W_{f_c} , W_{d_c} , DI_{f_f} , DI_{f_c} , DI_{d_f} , DI_{d_c} , WC_m , WC_s , RS_f , RS_d , L_r and LAI of JY35 and JS206 variety, and W_{f_p} , W_{d_p} , DI_{f_r} and DI_{d_r} of JS206 variety, where L_r and LAI of JY35 and JS206, and W_{f_p} and W_{d_p} of JS206 variety, show a logarithmic increase, and other productivity indicators show a logarithmic decrease. $I_{logistic}$ is a logistic type indicator that shows a logistic trend with the increase in EAT, including W_{f_r} , W_{f_m} , W_{f_s} , W_{f_o} , W_{f_w} , Y_{f_f} , W_{d_r} , W_{d_m} , W_{d_s} , W_{d_o} , W_{d_w} , Y_{d_f} , V_m , V_p , V_s and H of the JY35 and JS206 variety, and W_{f_t} , W_{f_f} , W_{f_l} , W_{d_t} , W_{d_f} and W_{d_l} of the JS206 variety. Additionally, a, b, and c are model parameters that are related to the productivity characteristics of the variety (Table 1).

Table 1. CPSM model parameters, where a, b, and c are model parameters that are related to the productivity characteristics of the variety, and R^2 represents the coefficient of determination, which can reflect the significance of the relationship between productivity indicators and effective accumulated temperature.

Indicators		JY35				JS206			
		Parameter a	Parameter b	Parameter c	R^2	Parameter a	Parameter b	Parameter c	R^2
Fresh weight	W_{f_r}	−0.0061	2.8933	16	0.7581	−0.0055	2.0307	19.8	0.5520
	W_{f_t}	1.84	—	—	—	−0.0049	2.113	2.3	0.7280
	W_{f_f}	6.2	—	—	—	−0.004	1.6933	0.96	0.7919
	W_{f_m}	−0.0074	3.4524	271	0.8445	−0.0077	3.5879	346	0.8147
	W_{f_p}	45.29	—	—	—	20.111	−76.713	—	0.7462
	W_{f_s}	−0.0054	2.6581	387	0.7467	−0.0077	3.084	390	0.7762
	W_{f_c}	−1.219	8.3271	—	0.7143	−0.497	4.7939	—	0.4268
	W_{f_l}	122.03	—	—	—	−0.0066	2.0978	152	0.6172
	Y_{f_f}	−0.007	3.8839	1728	0.8017	−0.0053	3.8623	2687	0.8300
	W_{f_o}	−0.0062	2.3255	483	0.8286	−0.0053	2.5481	605	0.8997
	W_{f_w}	−0.0075	2.9448	493	0.7938	−0.005	2.3119	615	0.8757

Table 1. Cont.

Indicators		JY35				JS206			
		Parameter a	Parameter b	Parameter c	R ²	Parameter a	Parameter b	Parameter c	R ²
Dry weight	W_{d_r}	−0.0045	2.6354	1.9	0.9009	−0.0059	2.2191	2.3	0.6725
	W_{d_t}	0.17	—	—	—	−0.0054	2.2915	0.24	0.8679
	W_{d_f}	0.51	—	—	—	−0.0027	1.758	0.18	0.6439
	W_{d_m}	−0.0073	3.3909	21.9	0.6204	−0.0091	4.3325	37	0.904
	W_{d_p}	2.34	—	—	—	0.9171	−2.7791	—	0.4763
	W_{d_s}	−0.0058	3.0043	31.1	0.7594	−0.0087	3.9276	40	0.8756
	W_{d_c}	−0.056	0.4129	—	0.4437	−0.043	0.4206	—	0.2438
	W_{d_l}	18.32	—	—	—	−0.0056	1.4636	22.9	0.4831
	Y_{d_f}	−0.0068	3.7649	86	0.8267	−0.0049	3.7172	134	0.8966
	W_{d_o}	−0.0054	1.7622	47.5	0.5991	−0.0049	2.5227	70.6	0.8435
	W_{d_w}	−0.0054	1.7305	48.6	0.6206	−0.0047	2.3726	71.6	0.8227
Fresh weight distribution index	DI_{f_r}	2.92	—	—	—	−8.593	54.072	—	0.9530
	DI_{f_t}	0.48	—	—	—	0.4	—	—	—
	DI_{f_f}	−1.386	10.714	—	0.783	−0.175	1.374	—	0.4779
	DI_{f_m}	0.0515	18.687	—	0.9326	0.0382	30.872	—	0.9647
	DI_{f_p}	−0.0171	26.296	—	0.8475	−0.0146	23.453	—	0.6818
	DI_{f_s}	0.04	37.054	—	0.9648	0.0368	45.412	—	0.9904
	DI_{f_c}	−0.432	2.9996	—	0.9104	−0.273	2.149	—	0.5891
	DI_{f_l}	−0.0424	58.763	—	0.9656	−0.0271	45.874	—	0.9284
Dry weight distribution index	DI_{d_r}	3.07	—	—	—	−8.388	53.78	—	0.9581
	DI_{d_t}	0.42	—	—	—	0.36	—	—	—
	DI_{d_f}	−1.491	11.126	—	0.8081	−0.295	2.2449	—	0.6456
	DI_{d_m}	0.057	6.5602	—	0.9232	0.0448	21.346	—	0.9486
	DI_{d_p}	−0.0077	12.395	—	0.8106	−0.0063	11.409	—	0.6854
	DI_{d_s}	0.0513	14.376	—	0.9604	0.046	29.113	—	0.9632
	DI_{d_c}	−0.337	2.3807	—	0.8025	−0.14	1.1726	—	0.4905
	DI_{d_l}	−0.0524	81.271	—	0.9650	−0.0423	67.066	—	0.9494
Water content	WC_r	90.33	—	—	—	88.18	—	—	—
	WC_t	90.62	—	—	—	89.82	—	—	—
	WC_f	91.61	—	—	—	87.79	—	—	—
	WC_m	−2.112	105.5	—	0.9578	−1.174	97.974	—	0.9566
	WC_p	95.15	—	—	—	94.18	—	—	—
	WC_s	−1.716	103.69	—	0.9452	−1.308	99.301	—	0.9574
	WC_c	91.74	—	—	—	92.93	—	—	—
	WC_l	85.96	—	—	—	84.32	—	—	—
Stem volume	V_m	−0.0076	3.5463	335	0.8490	−0.0096	4.0482	277	0.8489
	V_p	−0.0053	0.2	69.5	0.3498	−0.0067	2.5265	81.4	0.4276
	V_s	−0.0079	3.5925	401	0.7947	−0.0066	2.959	382	0.7109
Root to shoot ratio	RS_f	−0.59	7.0313	—	0.1906	−5.881	39.809	—	0.8594
	RS_d	−0.6	7.2318	—	0.3080	−3.258	24.706	—	0.7441
Other indicators	L_r	5.082	−10.996	—	0.6460	2.8742	4.8263	—	0.8237
	H	−0.0078	3.5969	480	0.7863	−0.0079	2.544	373	0.8161
	LAI	0.2906	−0.5373	—	0.3677	0.3351	−1.0173	—	0.5779
	SLA	258.08	—	—	—	227.42	—	—	—

3. Results

This study obtained a comparison validation diagram that illustrated the measured and simulated values of the CPSM model based on EAT (Figure 1). In Figure 1, the solid line represents a 1:1 line, while the dashed line represents the error range. The close proximity of the simulated and measured values to the 1:1 line, within the error range, suggest a high level of consistency between the two. As shown in Figure 1, R² was between 0.34 and 0.99, NRMSE was between 0.44% and 19.64%, MRE was between 0.31% and 17.23%, and D value was between 0.71 and 1.00. Therefore, the CPSM model based on EAT had high simulation accuracy. According to NRMSE, the simulation accuracy of productivity indicators was in the order of WC, L_r , fresh weight distribution index (DI_{fw}), SLA, dry weight distribution index (DI_{dw}), H, LAI, Y_{d_f} , stem volume (V_{stem}), Y_{f_f} , organ fresh weight (W_{fw}), RS, and organ dry weight (W_{dw}). According to MRE, the simulation accuracy of productivity indicators was in the order of WC, L_r , SLA, DI_{fw} , LAI, DI_{dw} , H, RS, V_{stem} ,

W_{fw} , Y_{d-f} , Y_{f-f} , and W_{dw} . In summary, the simulation accuracy of CPSM model for WC , L_r , SLA , and DI_{fw} was extremely high, while the simulation accuracy of other productivity index models was high.

This study further analyzed the indicators and varieties of differences in CPSM model simulation accuracy. In terms of indicator differences, the NRMSE was between 0.12% and 37.79% and the MRE was between 0.11% and 32.67%. Based on the comprehensive analysis of NRMSE and MRE, the simulation accuracy of productivity indicators was in the order of WC_p , WC_s , WC_m , WC_c , WC_r , WCl , WCt , WCf , DI_{f-s} , DI_{d-l} , DI_{f-l} , DI_{d-s} , DI_{f-m} , L_r , DI_{d-m} , SLA , DI_{d-p} , DI_{f-p} , Wf_o ($A_{NM} = 9.83\%$), Wf_w ($A_{NM} = 10.56\%$), LAI , Wd_o , Wd_w , Wf_s , H , Vp , Wf_m , RSd , DI_{f-r} , DI_{d-r} , Wf_r , Wf_p , Vs , RSf , Vm , Wf_l , Y_{d-f} , Wd_p , Y_{f-f} , Wd_s , Wd_m , Wf_c , Wd_l , DI_{f-t} , DI_{f-c} , DI_{d-c} , Wd_r , Wf_f , DI_{d-f} ($A_{NM} = 19.59\%$), DI_{d-t} ($A_{NM} = 21.48\%$), DI_{f-f} , Wd_c , Wf_t , Wd_f ($A_{NM} = 24.35\%$) and Wd_t ($A_{NM} = 35.23\%$). There were, respectively 19 indicators (accounting for 34.55%), 30 indicators (accounting for 54.55%), 5 indicators (accounting for 9.09%), and 1 indicator (accounting for 1.82%) with extremely high, high, general, and poor model simulation accuracy. In terms of variety differences, the NRMSE of the JY35 variety was between 0.12% and 56.65% and the MRE was between 0.10% and 50.19%; the NRMSE of the JS206 variety was between 0.12% and 35.86% and the MRE was between 0.11% and 36.18%. The JY35 variety ($A_{NM} = 10.44 \pm 8.49\%$) had higher simulation accuracy than the JS206 variety ($A_{NM} = 13.44 \pm 8.50\%$). The advantageous productivity index model of JY35 variety included W_{fw} , Y_{f-f} , W_{dw} , DI_{fw} , DI_{dw} , WC , V_{stem} , RS , L_r , H , and LAI , and the advantageous productivity index model of JS206 variety included Y_{d-f} and SLA . In the W_{fw} model, the advantageous productivity index of JY206 variety was W_{f-t} , W_{f-p} , W_{f-c} and W_{f-l} . In the W_{dw} model, the advantageous productivity index of JY206 variety was W_{d-t} , W_{d-p} and W_{d-l} . In DI_{fw} model, the advantageous productivity index of JY206 variety was DI_{f-m} and DI_{f-s} . In DI_{dw} model, the advantageous productivity index of JY206 variety was DI_{d-t} , DI_{d-m} and DI_{d-s} . In WC model, the advantageous productivity index of JY206 variety was WC_c . In summary, CPSM model simulation accuracy had the indicators and varieties differences (Table 2).

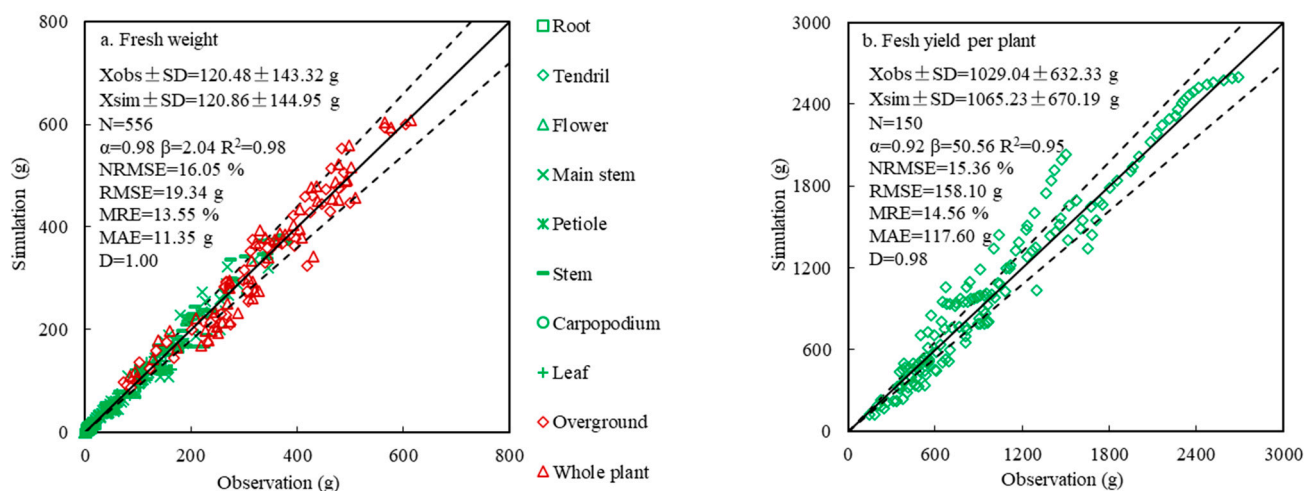


Figure 1. Cont.

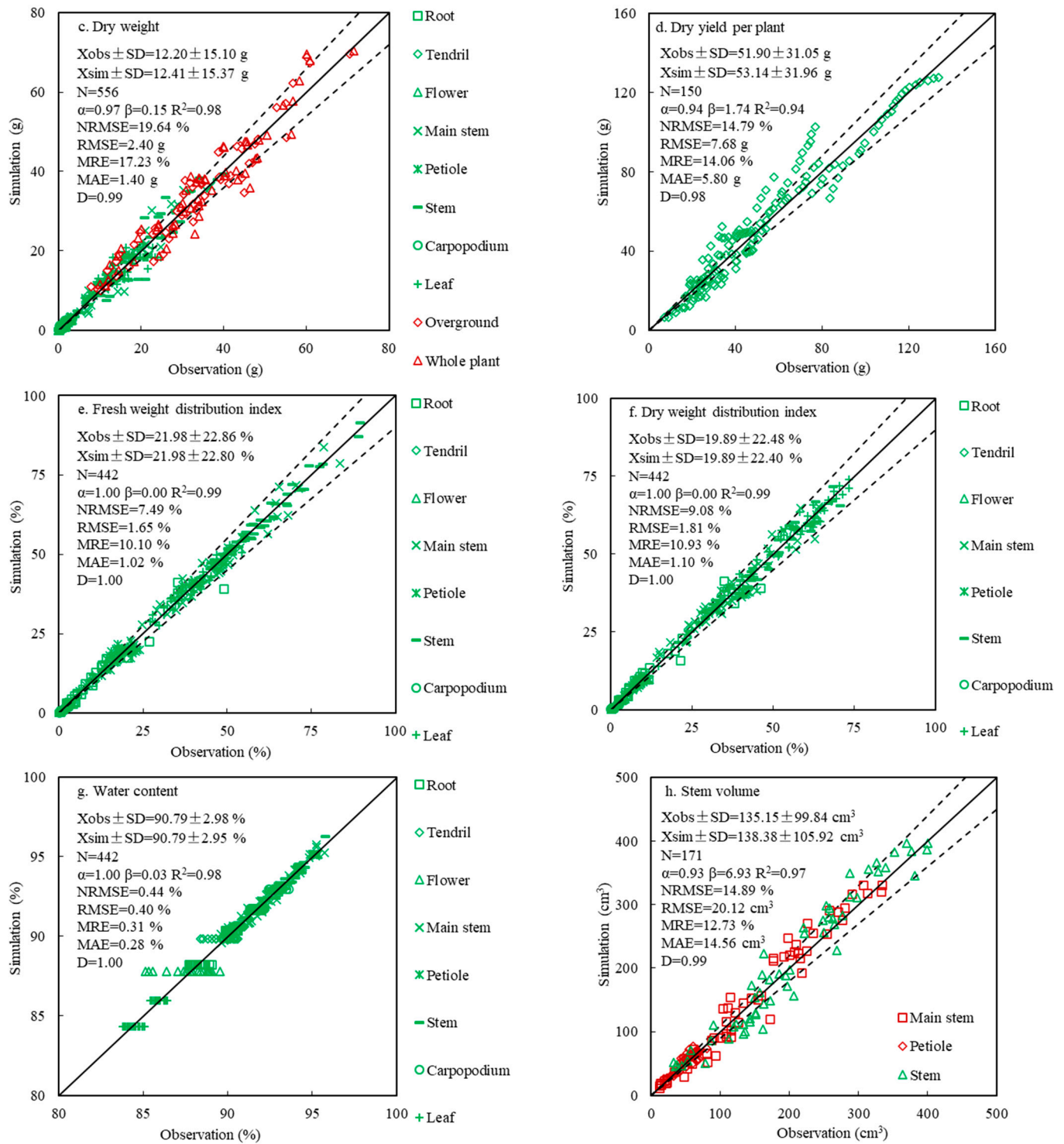


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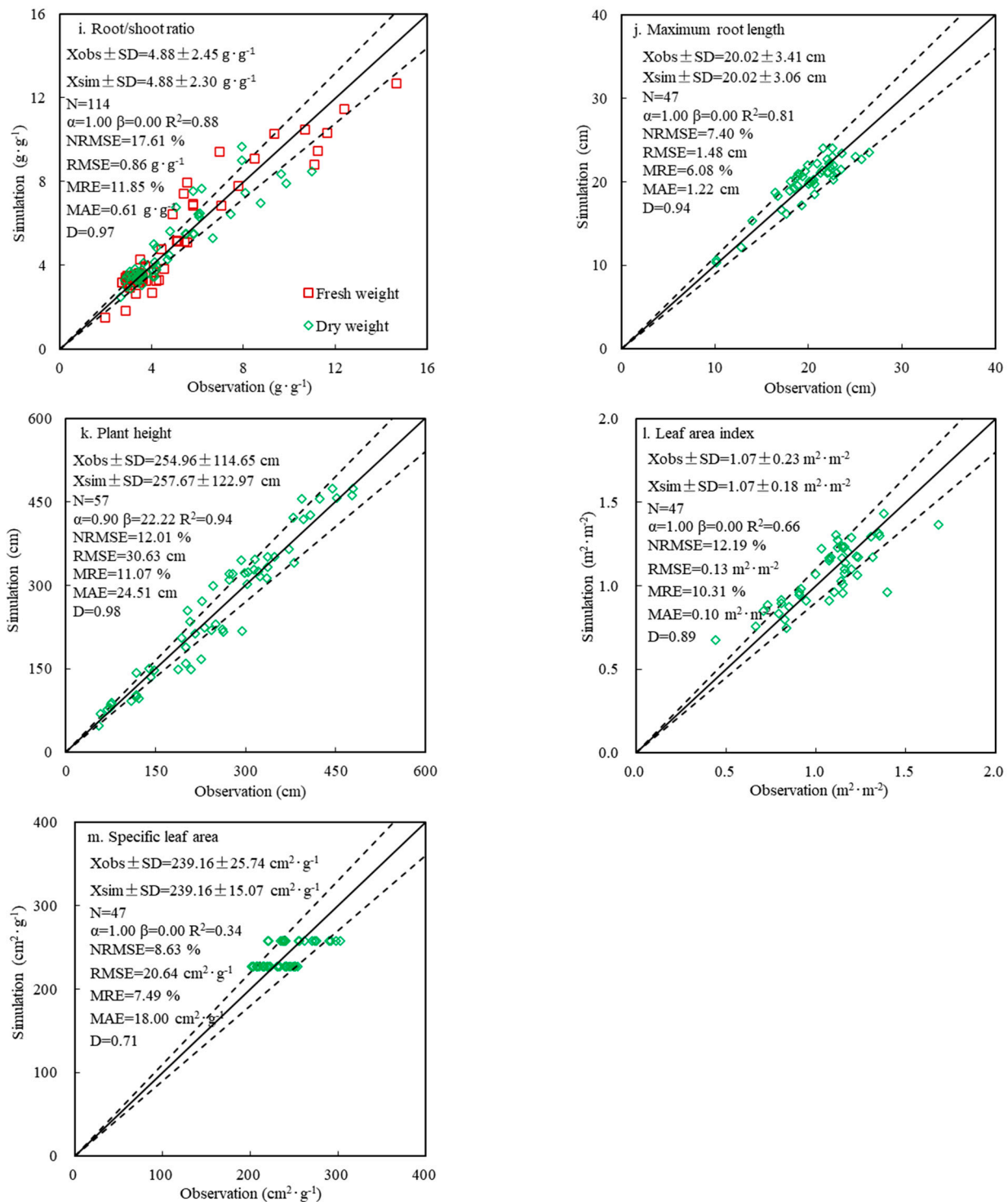


Figure 1. Comparison between measured and simulated values of CPSM model, including fresh weight (a), fresh yield per plant (b), dry weight (c), dry yield per plant (d), fresh weight distribution index (e), dry weight distribution index (f), water content (g), stem volume (h), root to shoot ratio (i), maximum root length (j), plant height (k), leaf area index (l) and specific leaf area (m).

Table 2. Statistics of measured and simulated values of CPSM model, where * indicates that the model had an extremely high simulation effect, # indicates that the model had a high simulation effect, \$ indicates that the model had a general simulation effect, ! indicates that the model had a poor simulation effect, and @ indicates the disadvantageous variety of the model.

Indicator		Unit	JY35				JS206			
			RMSE	NRMSE/%	MAE	MRE/%	RMSE	NRMSE/%	MAE	MRE/%
Fresh weight (Figure 1a,b)	W_{f_r}	g	0.92	11.23 #	0.78	9.62 *	1.56 @	16.36 #@	1.33 @	14.61 #@
	W_{f_t}	g	0.54 @	29.26 \$@	0.48 @	28.88 \$@	0.18	18.1 #	0.14	16.14 #
	W_{f_f}	g	1.05 @	16.97 #	0.92 @	15.19 #	0.11	21.19 \$@	0.09	23.55 \$@
	W_{f_m}	g	14.2	8.47 *	11.35	6.96 *	25.32 @	18.5 #@	18.09 @	15.36 #@
	W_{f_p}	g	7.26 @	16.03 #@	6.09 @	13.29 #@	5.03	12.09 #	4.13	10.99 #
	W_{f_s}	g	19.75	9.08 *	16.64	8.63 *	27.26 @	14.06 #@	22.5 @	13.89 #@
	W_{f_c}	g	0.18	21.41 \$@	0.14	17.52 #@	0.28 @	15.95 #	0.21 @	11.89 #
	W_{f_l}	g	21.42 @	17.56 #@	17.76 @	14.54 #@	11.31	13.09 #	9.82	11.8 #
	Y_{f_f}	g	119.77	14.89 #	96.76	14.44 #	193.65 @	14.98 #@	142.06 @	14.69 #@
	W_{f_o}	g	27.64	8.15 *	22.78	7.26 *	36.85 @	12.15 #@	29.08 @	11.75 #@
	W_{f_w}	g	33.95	9.73 *	27.81	8.87 *	36.84 @	11.45 #@	31.17 @	12.17 #@
Dry weight (Figure 1c,d)	W_{d_r}	g	0.08	9.83 *	0.07	8.35 *	0.30 @	29.16 \$@	0.22 @	26.59 \$@
	W_{d_t}	g	0.1 @	56.65 !@	0.07 @	50.19 !@	0.02	18.93 #	0.01	15.14 #
	W_{d_f}	g	0.07 @	13.65 #	0.06 @	11.71 #	0.03	35.86 !@	0.02	36.18 !@
	W_{d_m}	g	1.51	11.28 #	1.28	10.62 #	2.9 @	22.72 \$@	2.09 @	18.41 #@
	W_{d_p}	g	0.41 @	17.73 #@	0.35 @	14.8 #@	0.34	12.93 #	0.29	12.04 #
	W_{d_s}	g	2	11.82 #	1.67	10.53 #	3.62 @	21.7 \$@	2.73 @	17.81 #@
	W_{d_c}	g	0.02	21.34 \$	0.01	16.76 #	0.04 @	27.7 \$@	0.04 @	25.15 \$@
	W_{d_l}	g	3.37 @	18.4 #@	2.88 @	16.48 #	2.5	17.21 #	2.19	16.62 #@
	Y_{d_f}	g	5.95	14.82 #@	4.76	14.11 #@	9.3 @	14.16 #	7.02 @	14 #
	W_{d_o}	g	3.7	10.77 #	3.22	9.64 *	4.19 @	12.69 #@	3.23 @	12.01 #@
	W_{d_w}	g	3.71	10.49 #	3.21	9.37 *	4.56 @	13.06 #@	3.56 @	12.28 #@
Fresh weight distribution index (Figure 1e)	DI_{f_r}	%	0.29	9.77 *	0.24	8.45 *	2.67 @	18.92 #@	1.71 @	12.96 #@
	DI_{f_t}	%	0.08	17.12 #	0.07	14.23 #	0.09 @	21.78 \$@	0.07	16.79 #@
	DI_{f_f}	%	0.3 @	13.65 #	0.27 @	13.45 #	0.1	33.5 !@	0.08	27.6 \$@
	DI_{f_m}	%	3.17 @	6.61 *@	2.63 @	5.83 *@	2.42	5.4 *	2.02	4.43 *
	DI_{f_p}	%	1.54	8.77 *	1.2	6.84 *	2.27 @	13.02 #@	1.88 @	10.52 #@
	DI_{f_s}	%	1.84 @	3.14 *@	1.59 @	2.71 *@	1.11	1.96 *	0.88	1.48 *
	DI_{f_c}	%	0.04	12 #	0.03	11.87 #	0.12 @	25.81 \$@	0.11 @	22.48 \$@
	DI_{f_l}	%	1.75	4.25 *	1.42	3.72 *	1.88 @	5.22 *@	1.61 @	4.92 *@
Dry weight distribution index (Figure 1f)	DI_{d_r}	%	0.31	10.16 #	0.28	9.33 *	2.49 @	17.75 #@	1.75 @	13.86 #@
	DI_{d_t}	%	0.1 @	24.04 \$@	0.08 @	20.89 \$@	0.08	21.95 \$	0.07	19.04 #
	DI_{d_f}	%	0.32 @	15.7 #	0.24 @	11.59 #	0.11	27.74 \$@	0.09	23.34 \$@
	DI_{d_m}	%	3.79 @	9.72 *@	3.22 @	9.28 *@	2.54	7.14 *	2.05	5.95 *
	DI_{d_p}	%	0.75	9.09 *	0.63	7.59 *	1.03 @	11.7 #@	0.82 @	8.95 *@
	DI_{d_s}	%	2.46 @	5.96 *@	2.06 @	5.08 *@	2.22	5.13 *	1.88	4.23 *
	DI_{d_c}	%	0.05	17.52 #	0.04	13.33 #	0.08 @	23.53 \$@	0.06 @	20.42 \$@
	DI_{d_l}	%	2.16	3.63 *	1.74	2.98 *	2.47 @	4.74 *@	2.07 @	4 *@
Water content (Figure 1g)	WC_r	%	0.24	0.26 *	0.21	0.23 *	0.41 @	0.46 *@	0.37 @	0.42 *@
	WC_t	%	0.23	0.25 *	0.21	0.23 *	0.57 @	0.63 *@	0.45 @	0.5 *@
	WC_f	%	0.23	0.25 *	0.19	0.21 *	1.21 @	1.38 *@	0.94 @	1.08 *@
	WC_m	%	0.2	0.22 *	0.17	0.18 *	0.35 @	0.39 *@	0.3 @	0.32 *@
	WC_p	%	0.11	0.12 *	0.09	0.1 *	0.12 @	0.12 *	0.1 @	0.11 *@
	WC_s	%	0.2	0.21 *	0.16	0.17 *	0.29 @	0.31 *@	0.25 @	0.27 *@
	WC_c	%	0.3 @	0.33 *@	0.27 @	0.29 *@	0.28	0.3 *	0.21	0.22 *
	WC_l	%	0.31	0.36 *	0.26	0.31 *	0.4 @	0.48 *@	0.36 @	0.42 *@
Volume (Figure 1h)	V_m	cm ³	15.56	8.14 *	12.59	7.43 *	24.26 @	22.62 \$@	18.2 @	18.39 #@
	V_p	cm ³	4.03	6.42 *	3.27	5.63 *	9.11 @	19.37 #@	7.82 @	16.57 #@
	V_s	cm ³	21.65	9.14 *	18.46	9.34 *	31.83 @	18.84 #@	26.72 @	18.45 #@
Root to shoot ratio (Figure 1i)	RS_f	g·g ⁻¹	0.39	11.5 #	0.31	9.27 *	1.22 @	18.49 #@	0.97 @	16.61 #@
	RS_d	g·g ⁻¹	0.36	10.26 #	0.3	8.59 *	1.08 @	18.05 #@	0.83 @	12.73 #@
Other indicators (Figure 1j–m)	L_r	cm	1.26	6.64 *	1.05	5.75 *	1.6 @	7.77 *@	1.33 @	6.29 *@
	H	cm	25.81	8.27 *	21.35	7.49 *	34.66 @	17.35 #@	27.56 @	14.52 #@
	LAI	m ² ·m ⁻²	0.11	9.13 *	0.09	7.02 *	0.14 @	14.49 #@	0.11 @	12.36 #@
	SLA	cm ² ·g ⁻¹	25.53 @	9.89 *@	22.21 @	8.63 *@	16.92	7.44 *	15.38	6.79 *

This study further comprehensively analyzed the interaction between indicators and variety factors differences of CPSM model simulation accuracy. As shown in Figure 2, the statistical proportions of RMSE, NRMSE, MAE, and MRE were, respectively, from 9.48% to 90.52%, from 15.34% to 84.66%, from 8.91% to 91.09%, and from 16.28% to 83.73%. The statistical proportions of JY35 and JS206 varieties were, respectively, from 16.10% to 80.65% and from 19.35% to 83.90%. Among them, the number of superior productivity indicators for JY35 variety was 39 (accounting for 70.91%), and the statistical proportions of superior productivity indicators was in the order of WCf, Wd_r, Dlf_r, Dld_r, Vp, Dlf_c, Wct, RSf, RSd, Vm, Wd_c, Wf_m, Wd_m, Wcm, WCr, Wd_s, Vs, H, Wf_r, WCs, Dlf_p, Dld_c, Wf_s, LAI, Wf_o, WCl, Dld_p, Yf_f, Dld_l, Wd_w, Yd_f, Lr, Dlf_l, Wf_w, Dlf_t, Wd_o, WCp, Wf_c and Wd_f. The number of superior productivity indicators for the JS206 variety was 16 (accounting for 29.09%), and the statistical proportions of superior productivity indicators was in the order of Wd_t, Wf_t, Wf_f, Dlf_s, Wf_l, Dld_m, SLA, Wf_p, Dlf_m, Wd_p, Wcc, Dld_f, Wd_l, Dlf_f, Dld_t and Dld_s.

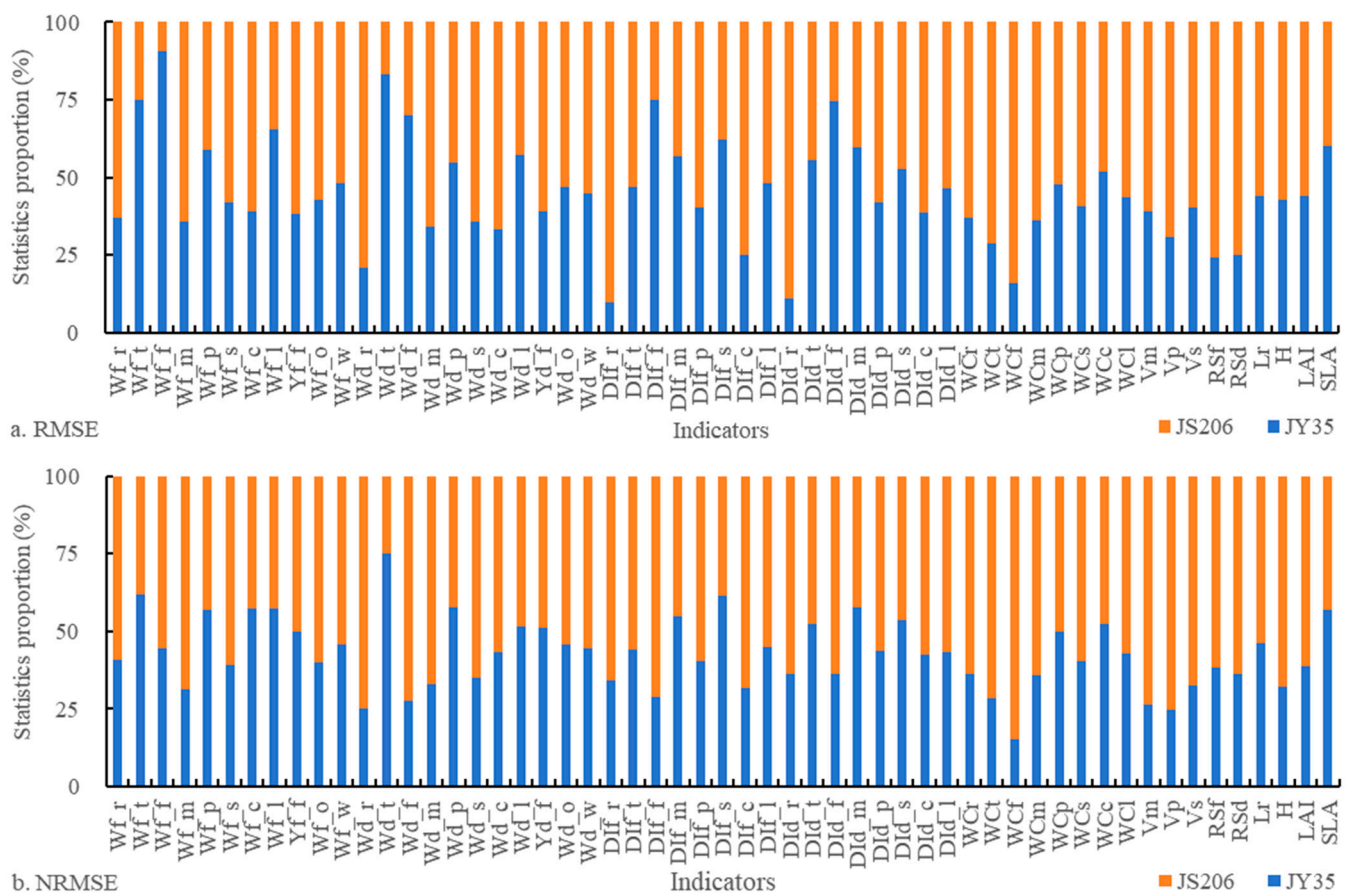


Figure 2. Cont.

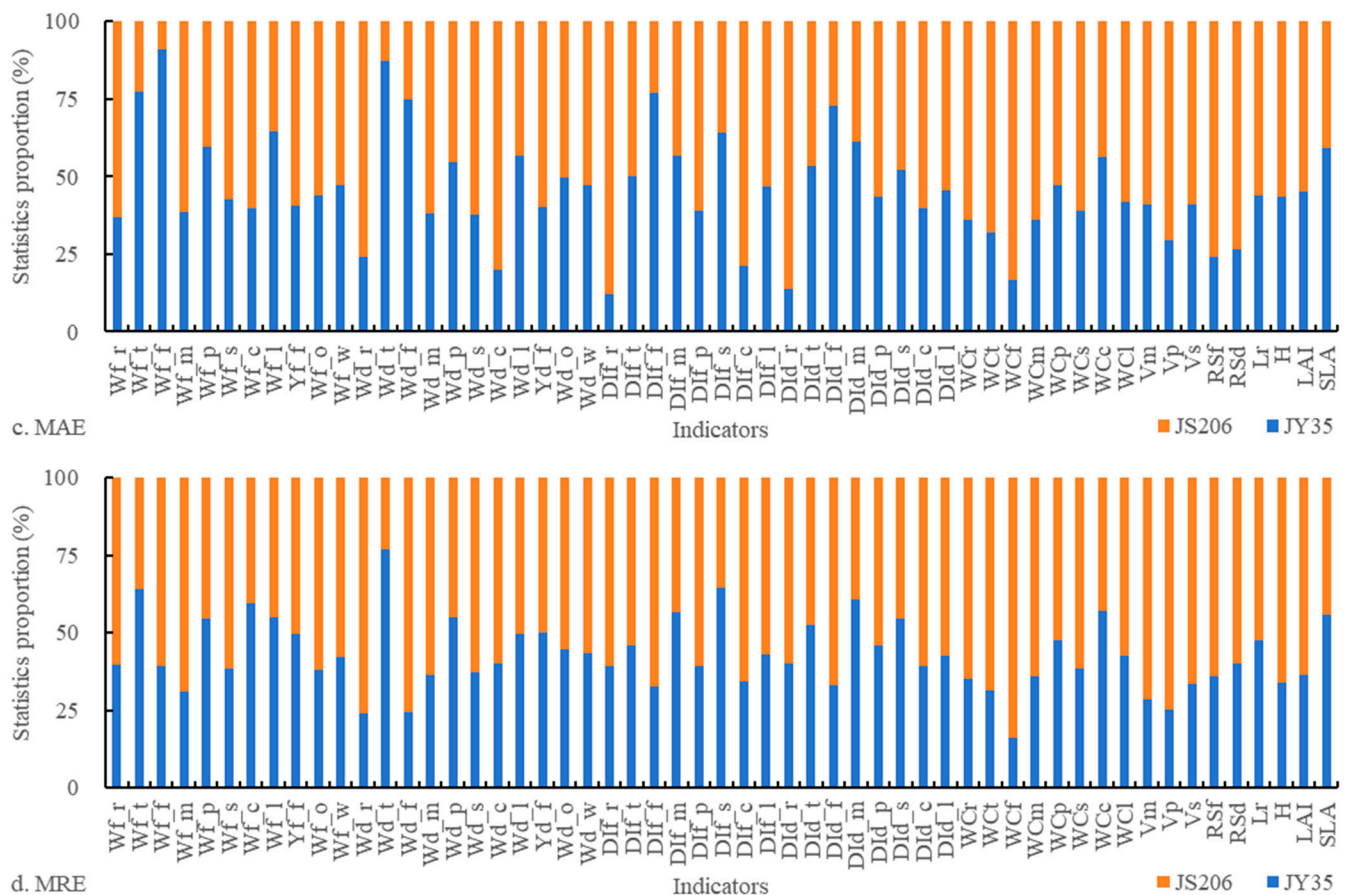


Figure 2. The proportion of measured and simulated statistical values in CPSM model, including RMSE (a), NRMSE (b), MAE (c) and MRE (d).

4. Discussion

The Cucumber Productivity Simulation Model (CPSM), based on effective accumulated temperature (EAT), was developed in this study to accurately simulate the dynamic process of cucumber productivity in a solar greenhouse. It was compared to general vegetable horticultural crop growth models such as HORTISIM [24], SIMULSERRE [25], TOMGRO [26] and TOMSIM [27]. Although these models can quantitatively simulate the development and phenological stages of horticultural crops, organ initiation and growth, photosynthesis and biomass accumulation, assimilate allocation and yield quality formation, there are challenges related to their adoption due to the complexity and availability of the parameters involved. For instance, the process parameters of photosynthesis and respiration need to be considered. Therefore, prior to using these models, extensive experimental data collection is necessary for parameter localization. CPSM utilizes easily accessible temperature data as its input, allowing for precise and detailed simulation of productivity indicators for cucumber production in a solar greenhouse. This research lays a theoretical foundation and provides technical support to guide intelligent production management, efficient utilization of agricultural resources, and climate change productivity assessment in solar greenhouse cucumber production. The distinctive feature of this study lies in the quantitative and detailed description of the dynamic changes in cucumber productivity indicators based on EAT. These indicators primarily include W_{fw} , W_{dw} , Y_{f-f} , Y_{d-f} , DI_{fw} , DI_{dw} , WC , V_{stem} , RS , LA , LAI , SLA , L_r and H . Furthermore, key crop parameters for different cucumber varieties were determined and the differences in simulation accuracy, variety, and interactive effects were analyzed.

The simulated values of different productivity indicators in the productivity model constructed in this study show an NRMSE ranging from 0.44% to 19.64% and an MRE

ranging from 0.31% to 17.23%. These results demonstrate that the CPSM, based on EAT, has a high level of simulation accuracy. The model takes into consideration the impact of crop variety and temperature on crop productivity. The simulation accuracy of the CPSM is generally consistent with other crop productivity models based on EAT in previous studies [13,20,22,23]. Furthermore, our analysis reveals that the NRMSE of simulated values compared to measured values ranging from 0.12% to 37.79% in terms of indicator-based differences, and the MRE ranges from 0.11% to 32.67%. In terms of variety-based differences, the JY35 variety ($10.44 \pm 8.49\%$) shows higher simulation accuracy than the JS206 variety ($13.44 \pm 8.50\%$), indicating that the CPSM exhibits variability in simulation accuracy for different indicators and varieties. The CPSM has advantages such as easily obtainable input data and high extrapolation ability. However, the CPSM constructed based on EAT has some limitations in modeling principles. Firstly, it only considers temperature as a single factor in simulating the process of productivity, which may cause simulation distortion and model errors. Secondly, the statistical EAT is based on daily average temperature and does not consider the daily temperature variations. This neglects the impact of time periods where temperatures may exceed or fall below the biological lower temperature limit but still contribute to accumulated temperature values, which may affect productivity. Thirdly, different crop varieties have different threshold temperatures, and this study lacks the determination of baseline temperature indicators for the developmental stages of the tested varieties. This could lead to inaccurate estimation of accumulated temperatures and, consequently, result in errors in CPSM simulation. Lastly, there are multiple factors that influence the productivity process, including biological factors such as species and variety types, physiological controls [12,13], as well as environmental factors such as light [12,33], water [37], fertilizer [37], pests and diseases [38], natural disasters [39], and growth regulators [40]. These factors could affect the effectiveness and reliability of the CPSM in practical applications of crop production. In conclusion, while the CPSM based on EAT demonstrates high simulation accuracy and certain advantages, it also has limitations in its modeling principles, which may introduce errors in simulation results. Consideration of additional factors and improvements in determining baseline temperature indicators for different variety development stages could enhance the validity and reliability of the CPSM in practical crop production applications.

5. Conclusions

(1) The Cucumber Productivity Simulation Model (CPSM) can dynamically and meticulously simulate the formation process of different productivity indicators in cucumber. There is a significant correlation between productivity indicators and effective accumulated temperature (EAT). The normalized root mean square error (NRMSE) of the CPSM model varied between 0.44% and 19.64%, while the mean relative error (MRE) ranged from 0.31% to 17.23%. The productivity indicator models for organ water content, maximum root length, specific leaf area, and organ fresh weight distribution index exhibited exceptional simulation accuracy. The simulation accuracy of other productivity indicator models was high.

(2) The model's simulation accuracy exhibited variations in indicators and varieties. Out of the total indicators, 19 indicators (34.55%) had remarkably high simulation accuracy, while 30 indicators (54.55%) had high simulation accuracy. The JY35 variety exhibited greater simulation accuracy ($10.44 \pm 8.49\%$) compared to the JS206 variety ($13.44 \pm 8.50\%$). The statistical proportions (RMSE, NRMSE, MAE, and MRE) of JY35 and JS206 varieties were, respectively, from 16.10% to 80.65% and from 19.35% to 83.90%. The JY35 variety had 39 advantageous productivity indicators, accounting for 70.91% of the total, while the JS206 variety had 16 indicators, accounting for 29.09%.

Regarding the future research and application directions of the CPSM, several aspects can be explored. Firstly, it is important to deepen the coupling mechanism and methods between the model and "3S" technologies [41] in order to enhance the productivity simulation accuracy in extreme climate environments and different production manage-

ment modes. Secondly, there is a need to investigate estimation methods for crop genetic parameters based on functional gene physiological effects and genetic regulations. This should include exploring the interaction mechanisms and quantitative methods between major trait gene effects and environmental effects [42], leading to the development of an integrated simulation model covering “gene effects–genetic parameters–phenotypic characteristics–productivity formation”. Thirdly, integrating relevant algorithms from artificial intelligence decision-making and crop phenotypic monitoring technologies [43], it is essential to construct an intelligent agricultural production management decision support system. This system can provide intelligent tools like optimized crop canopy design. Lastly, developing a productivity model support system that incorporates multiple algorithms is necessary to reduce the uncertainty caused by model parameters and structure on simulation results [12].

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