Simulation and evaluation of tomato growth by AquaCrop model under different agricultural waste materials

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Abstract: This study aimed to enhance the utilization of agricultural waste and identify the most suitable agricultural waste materials for tomato cultivation. It utilized a locally modified substrate labeled as CK, along with five different groups of agricultural waste materials, designated as T1 (organic fertilizer: loessial soil: straw in a ratio of 4:5:1), T2 (organic fertilizer: loessial soil: straw: grains in a ratio of 3:5:1:1), T3 (organic fertilizer: loessial soil: straw: grains in a ratio of 2:5:1:2), T4 (organic fertilizer:loessial soil:straw:grains in a ratio of 1:5:1:3), and T5 (loessial soil:straw:grains in a ratio of 5:1:4), the AquaCrop model was employed to validate soil water content and tomato growth and yield under these treatments. Furthermore, a multi-objective genetic algorithm was employed to determine the optimal agricultural waste materials that would ensure maximum tomato yield, water use efficiency (WUE), partial factor productivity of fertilizer (PFP) and sugar-acid ratio. The results indicated that the AquaCrop model reasonably simulated volumetric soil water content, tomato canopy cover, and biomass, with root mean square error (RMSE) ranges of 20.0-69.4 mm, 15.2%-25.1%, and 1.093-3.469 t/hm^2, respectively. The CK group exhibited an R-squared (R^2) value of 0.63 for volumetric soil water contents, while the ratio scenarios showed R^2 values exceeding 0.80. The multi-objective genetic optimization algorithm identified T5 as the optimal ratio scenario, resulting in maximum tomato yield, WUE, PFP, and quality. This study offers a theoretical foundation for the efficient utilization of agricultural wastes and the production of high-quality fruits and vegetables.

Keywords: agricultural waste materials, AquaCrop model, NSGA-II algorithm, tomato, quality
DOI: 10.25165/j.ijabe.20241705.8539

Citation: Zhou C Q, Zhao W J, Li H L, Ma F, Wu K Q. Simulation and evaluation of tomato growth by AquaCrop model under different agricultural waste materials. Int J Agric & Biol Eng, 2024; 17(5): 112–119.

1 Introduction

With the rapid development of agriculture in China, agricultural wastes such as straw and vegetable residues account to over 1×10^9 t/a[1]. Improper disposal and underutilization of agricultural waste can lead to agricultural ecosystem destruction and environmental degradation[2]. The application of organic nutrients has been shown to significantly increase crop yields, which is crucial for sustainable agricultural production[3,4]. Furthermore, utilizing agricultural waste can enhance the physicochemical fertility of the soil, reduce carbon emissions, and create a conducive growth environment for plants, thereby further increasing its application value[5-7]. Therefore, studying the distribution patterns of crop yields and soil moisture under different proportions of straw and organic fertilizer can help determine the optimal application ratios of agricultural waste materials, thereby enhancing the overall efficiency of agricultural waste utilization.

The AquaCrop growth model, developed by the Food and Agriculture Organization (FAO) of the United Nations, can simulate aboveground biomass and yield using crop canopy cover, harvest index, and soil properties[8,9]. Several researchers have extensively utilized the AquaCrop model to simulate yields and biomass across various irrigation regimes and crops, such as wheat[10], tomato[11,12], maize[13,14], cotton[15,16], and rice[17]. These studies have consistently shown the AquaCrop model to be accurate in simulating crop growth. Ran et al.[18] highlighted the importance of calibration parameters, like reference harvest index HI_0 in improving the simulation of normalized dry matter water productivity (WP*) and harvest index (HI) under different water stress conditions. Dubey et al.[19] used the AquaCrop crop model to evaluate the impact of climate change on aboveground biomass and predict yields for wheat, barley, and maize over the next 30 years. Song et al.[20] optimized irrigation scheduling under different film treatments and typical years using a multi-objective simulation-optimization model based on the AquaCrop model and multi-objective genetic algorithm (NSGA-II). Nyathi et al.[21]conducted experiments to calibrate maximum canopy cover and normalized dry matter water productivity (WP*) for three-leaf vegetables using the AquaCrop model, showing good fit under both sufficient and severe water deficit conditions. Adeboye et al.[22]demonstrated the accuracy of the growth model in simulating the canopy cover, aboveground biomass, and yield of soybean in different seasons. Takács et

Received date: 2023-09-19 **Accepted date:** 2024-08-07
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al.[23]utilized the AquaCrop model to assess the simulation accuracy of tomato biomass and yield in the continental climate of the Carpathian Basin, focusing on the relationship between climate and water.

Previous research on AquaCrop model has primarily concentrated on simulation of canopy cover, aboveground biomass and yield of wheat, maize, and cotton[10,12,13,16], often utilizing crop, water, and salt parameters to refine the growth model. Nonetheless, there is limited knowledge on the impact of organic fertilizer and straw on the simulation of tomato yield and biomass, as well as WUE and PFP. This study aimed to: 1) calibrate and validate the AquaCrop model for tomato yield, canopy cover, soil water contents, and biomass using various agricultural waste materials; 2) assess tomato quality under different agricultural waste materials; 3) identify suitable agricultural waste materials through the non-dominated sorting genetic algorithm (NSGA-II) to optimize tomato yield, biomass, WUE, and PFP. The findings of this study offer a scientific foundation for enhancing the utilization of agricultural waste and promoting high-quality tomato production.

2 Materials and methods

2.1 Experimental site and description

The experimental area is situated in Lanzhou New Area, characterized by a temperate semi-arid continental climate with an annual average temperature of 6.9°C and annual average precipitation varying from 300 to 350 mm. The study was conducted at the modern agricultural demonstration park of Lanzhou New District (103°42′E, 36°32′N) during the periods of July to November in both 2020 and 2021. The experiment focused on tomato cultivation (*Ai ji* 3041) under fertigation conditions utilizing a drip irrigation system.

2.2 Experimental methods

In this study, organic fertilizer, straw, and distillers grains were applied to tomato plants using five different ratios of inputs to loessial soil. These ratios were labeled as T1 (organic fertilizer: loessial soil:straw in a ratio of 4:5:1), T2 (organic fertilizer:loessial soil:straw:grains in a ratio of 3:5:1:1), T3 (organic fertilizer:loessial soil:straw:grains in a ratio of 2:5:1:2), T4 (organic fertilizer:loessial soil:straw:grains in a ratio of 1:5:1:3), and T5 (loessial soil:straw:grains in a ratio of 5:1:4). The control group (CK) consisted of a locally modified substrate. Water and fertilizer application rates were determined based on the study by Zhao et al.[24]. Each treatment received 60% ET_0 for irrigation, with N-P_2O_5-K_2O fertilizer applied at a rate of 180.0-88.0-121.2 kg/hm^2. Tomato plants were transplanted into the agricultural waste materials using a double-long grazing film planting method and were randomly arranged. Each plot contained fifteen plants, spaced 50 cm apart in rows and 35 cm apart within rows. Water and fertilizer were applied at specific growth stages of the tomato plants, namely 7, 18, 30, 49, 56, and 70 d after planting. Notably, days 49, 56, and 70 corresponded to the first, middle, and last fruit development stages. The experimental layout is illustrated in Figure 1.

2.3 Soil properties and determination methods

2.3.1 Soil moisture and salt contents

Soil samples were collected prior to the commencement of the experiment.

The soil moisture content was initially determined using the gravimetric method, followed by the calculation of volumetric soil water content (θ):

$$\theta = \gamma \frac{m_1 - m_0}{m_0} \times 100\% \tag{1}$$

where, γ is the soil bulk density, g/cm^3; m_1 is the weight of the wet soil, g; m_0 is the weight of the dry soil, g.

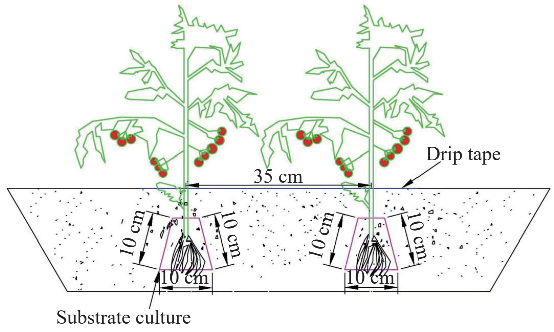


Figure 1 Experimental layout used in this study

Additionally, the pH and electrical conductivity of the soil were assessed using a PHSJ-4F pH meter (Century Ark Technology Co., Ltd., Chengdu, China) and DDS-307A conductivity meter (Century Ark Technology Co., Ltd., Chengdu, China), respectively, at both the start and the end of the experiment.

2.3.2 Determination of the tomato yield

Harvesting commenced at the onset of fruit ripening, occurring every 3-4 d. Six representative plants were randomly selected from each plot within the triplicate blocks to determine the tomato yield.

2.3.3 Calculation of water use efficiency and fertilizer partial productivity

Water use efficiency (WUE) was calculated in this study using the following formula:

$$\text{WUE} = Y/\text{ET} \tag{2}$$

where, Y is the tomato yield, kg/hm^2; ET is the evapotranspiration amount of tomato at each period, mm.

Partial factor productivity of fertilizer (PFP) was calculated using the following formula:

$$\text{PFP} = Y/F \tag{3}$$

where, F is the amount of fertilizer applied, kg/hm^2.

2.3.4 Crop canopy cover

Furthermore, 10 tomato plants were randomly selected at each growth stage to assess crop canopy cover. The length (B) and width (L) of the largest leaf were first measured, followed by the calculation of leaf area index (LAI) to determine canopy cover (CC) based on the provided formula:

$$\text{CC} = 1.005\left[1 - \exp(-0.6 \times \text{LAI})\right]^{1.2} \tag{4}$$

$$\text{LAI} = 0.75\rho \frac{\sum_{j=1}^{m}\sum_{j=1}^{n} L_{ij} \times B_{ij}}{m} \tag{5}$$

where ρ is the planting density, plant/hm^2; m is the number of measured plants; n is the total number of leaves of tomato plant j.

2.3.5 Quality determination

During the maturity stage of tomato fruit, the first and third spike fruits were harvested for quality assessment. Three replicates were chosen in each test area, with five representative tomato fruits of uniform maturity selected in each replicate. The average quality of the first and third spike fruits was considered as the overall quality of the conservation brick tomato. Hardness was assessed using a hardness meter (TOP Cloud-agri Technology Co., Ltd, Hangzhou, China); soluble solids were determined with a WAY-2S Abbe refractometer (ATAGO Co., LTD, Tokyo, Japan); total soluble sugar content was measured through anthrone colorimetry; and organic acid content was determined via acid-base titration.

2.4 Description of the AquaCrop model

2.4.1 AquaCrop model

This study utilized the AquaCrop crop growth model to simulate crop development in response to environmental conditions, soil conditions, and management practices. With its minimal input parameter requirements and ability to predict crop yields under various scenarios, the model effectively distinguishes between soil evaporation and crop transpiration using canopy cover, calculates aboveground biomass using transpiration and normalized dry matter water productivity, and controls final yield through harvest index. The core equations of the model are represented in Equations (6) and (7):

$$B = \mathrm{WP}^* \cdot \sum T \tag{6}$$

$$Y = \mathrm{HI} \times B \tag{7}$$

where, B is the aboveground biomass, t/hm^2; WP* is the normalized dry matter water productivity, derived from normalizing carbon dioxide concentration based on different water productivity efficiencies; T is the daily transpiration, mm; Y is the yield, t/hm^2; HI is the harvest index.

The input module of this model mainly includes six aspects: meteorological data, crop, soil, groundwater, field management, and initial conditions. Crop Module: This module requires information on crop variety, growing season, planting density, and phenological stages. Meteorological Module: This module needs data on rainfall, maximum and minimum temperatures, relative humidity, sunshine hours, and wind speed. Additionally, reference crop evapotranspiration and carbon dioxide concentration can be added as inputs. Soil Module: This module needs parameters like soil moisture content, field capacity, wilting coefficient, saturated hydraulic conductivity, and other soil properties. Groundwater Module: This module requires data on changes in groundwater depth. Field Management Module: This module needs information on mulching type, fertilizer application rates, irrigation amounts, and other management practices. Initial Conditions: This includes initial soil moisture content, canopy cover, aboveground biomass, and other relevant parameters.

2.4.2 Meteorological data

The meteorological data utilized in the AquaCrop model includes daily temperature and reference crop evapotranspiration ET_0. ET_0 was calculated using the Penman equation, considering maximum and minimum temperature values, sunshine hours, relative humidity, and wind speed. Meteorological parameters were sourced from the 'tavg1_2d_lnd_Nx' dataset obtained from the second Modern-Era retrospective analysis for Research and Applications version 2.

2.4.3 Crop data

The input variables related to crop data included the planting pattern, planting density, canopy cover, growth and development stages, and various indicators observed throughout the experiment. Additionally, the water stress parameters, normalized water productivity, and reference harvest index were calibrated and adjusted based on the range values specified in the AquaCrop model manual. The model parameters were calibrated using the experimental observation data from 2020 and validated using the experimental measurement data from 2021. The calibration results are detailed in Table 1.

Table 1 Calibration results of tomato crop parameters considered in the experiment

Parameter	Value
Initial canopy cover (CC_0)/%	0.40
Maximum canopy cover (CC_x)/%	85.00
Canopy growth coefficient (CGC)/%·d^{-1}	12.90
Crown degradation coefficient (CDC)/%·d^{-1}	0.25
Reference harvest index (HI_0)/%	65.00
Normalized dry matter water productivity (WP*)/g·m^{-2}	18.00
Crop coefficient (K_{cTr})	1.05
Maximum effective root depth (Z_{rmax})/m	0.70

2.4.4 Soil data

The hydraulic parameters required for the AquaCrop model include soil layer number, soil depth, saturated soil water content, soil field capacity, soil wilting coefficient, and saturated soil hydraulic conductivity. These parameter values can be found in Table 2.

Table 2 Hydraulic parameter values of experiment soil field

Treatment	Soil water content/%	Field capacity/%	Wilting coefficient/%
CK	46.0	31.0	11.5
T1	57.7	46.2	16.3
T2	50.1	41.2	14.1
T3	52.6	43.1	18.4
T4	56.4	41.2	16.3
T5	57.9	43.7	17.6

2.5 NSGA-II algorithm

This study employs the NSGA-II algorithm to find the Pareto solution of a multi-objective function in order to identify the most suitable agricultural waste materials for enhancing tomato growth. The NSGA-II algorithm is a rapid non-dominated multi-objective optimization technique that focuses on identifying Pareto optimal solutions and incorporates an elite reservation strategy. The degree of crowding is utilized to assess the distribution of system elements, prioritizing genes with uniform distribution and maximum information. The algorithm follows a sequence of six steps: population initialization, non-dominated sorting, calculation, selection, crossover and mutation, and recombination and selection based on crowding distance.

2.6 Model evaluation metrics

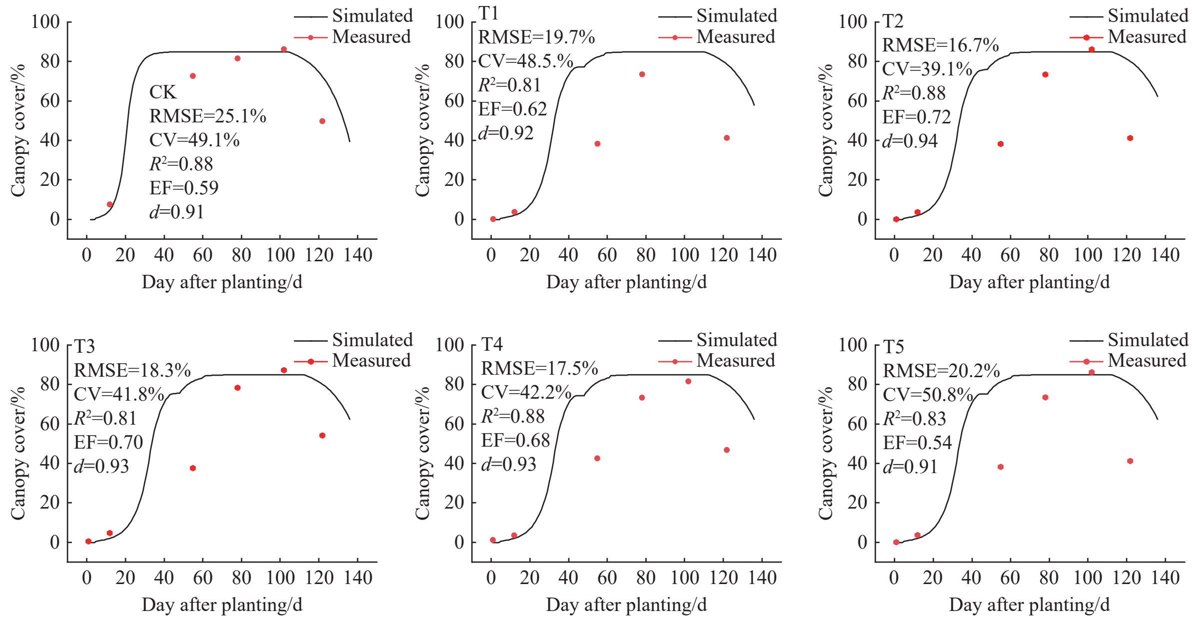
This study utilized various metrics such as root mean square error (RMSE), coefficient of determination (R^2), coefficient of consistency (d), Nash efficiency factor (EF), coefficient of variation (CV), and relative error (Pe) to assess the accuracy of model calibration and validation. A smaller RMSE and Pe indicate that R^2, d, and EF values are closer to 1, suggesting that the simulated values align closely with the measured results and the simulation outcomes are accurate.

3 Results

3.1 Calibration and validation of the AquaCrop model

3.1.1 Canopy cover

The AquaCrop model parameters were calibrated using tomato test data from 2020 (Table 1) and validated with data from 2021 (Table 2). As demonstrated in Figure 2, six groups of different agricultural waste materials were tested. The RMSE, R^2, d, EF, and CV range values calculated from the measured and simulated canopy cover under different ratios were 15.2%-25.1%, 0.81-0.88, 0.91-0.94, 0.54-0.72, and 25.6%-50.8%, respectively. The use of agricultural waste materials can enhance tomato growth by accelerating the growth process and increasing canopy cover. The simulation accuracy at the late growth stage was significantly higher than at the middle growth stage. The results indicate that the AquaCrop model may overestimate canopy cover during the middle and late stages of tomato growth.



Note: RMSE represents root mean square error; R^2 is the coefficient of determination; d is the coefficient of consistency; EF represents the Nash efficiency factor; CV is the coefficient of variation. Same below.

Figure 2 Validation results of tomato canopy cover in 2021

3.1.2 Biomass

The simulation results of tomato biomass accumulation under different ratios are illustrated in Figure 3, demonstrating an increase in biomass of post-transplanting. The results indicated a slight alignment between the simulated and measured values of tomato biomass. The RMSE for tomato bioaccumulation under various ratios ranged from 1.093 to 3.469 t/hm². The values of d, EF, and CV varied across different ratio scenarios, ranging from 0.81 to 0.99, 0.43 to 0.94, and 12.5% to 48.8%, respectively. Moreover, under equivalent irrigation rates, tomato canopy cover values in different ratio scenarios followed the sequence of T5>T2>T4>T3>T1>CK, highlighting the significant impact of agricultural waste materials on enhancing crop growth and development.

3.1.3 Soil water contents

The volumetric soil water content observed in the root zone during the tomato growth period under various ratios is depicted in Figure 4. Across all treatment scenarios, the RMSE, R^2, d, EF, and CV values ranged from 20.0 to 69.4 mm, 0.64 to 0.90, 0.48 to 0.94, –4.61 to 0.74, and 5.8% to 19.5%, respectively. The results indicated similar volumetric soil water contents levels at T2, T4, and T5 during the middle and late stages of growth, with the lowest content observed in the control (CK) plot. This suggests that the use of agricultural waste materials significantly contributes to soil water conservation. Towards the end of the growth period, the volumetric soil water content in different ratio scenarios followed the sequence of T3>T1>T5>T4>T2>CK.

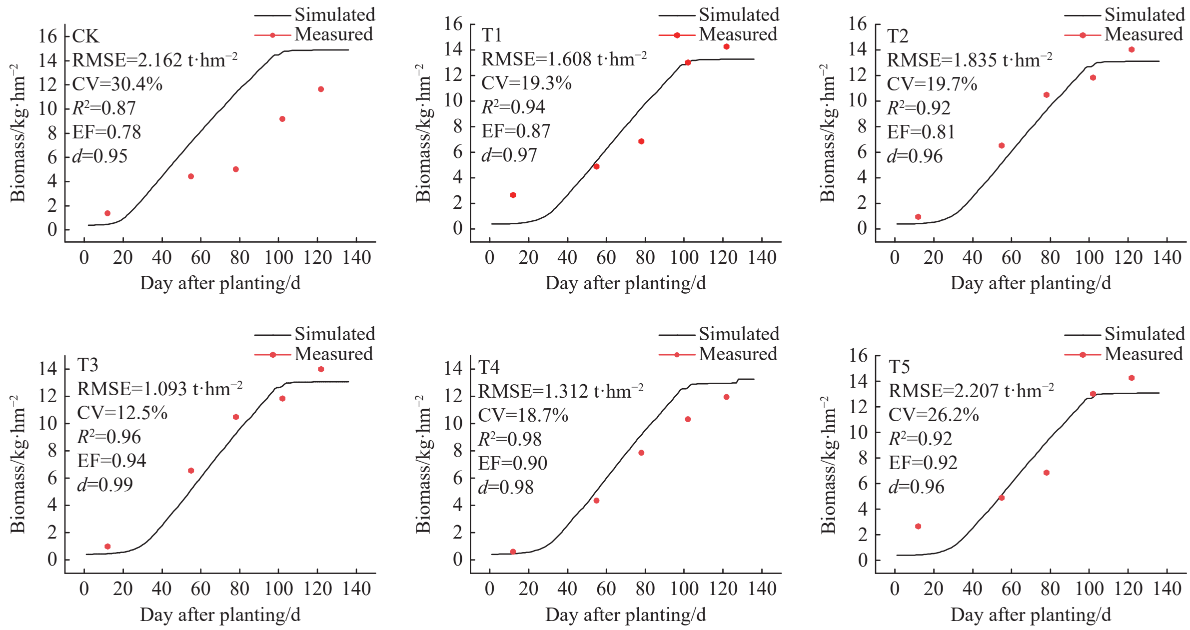


Figure 3 Validation results of tomato biomass simulation in 2021

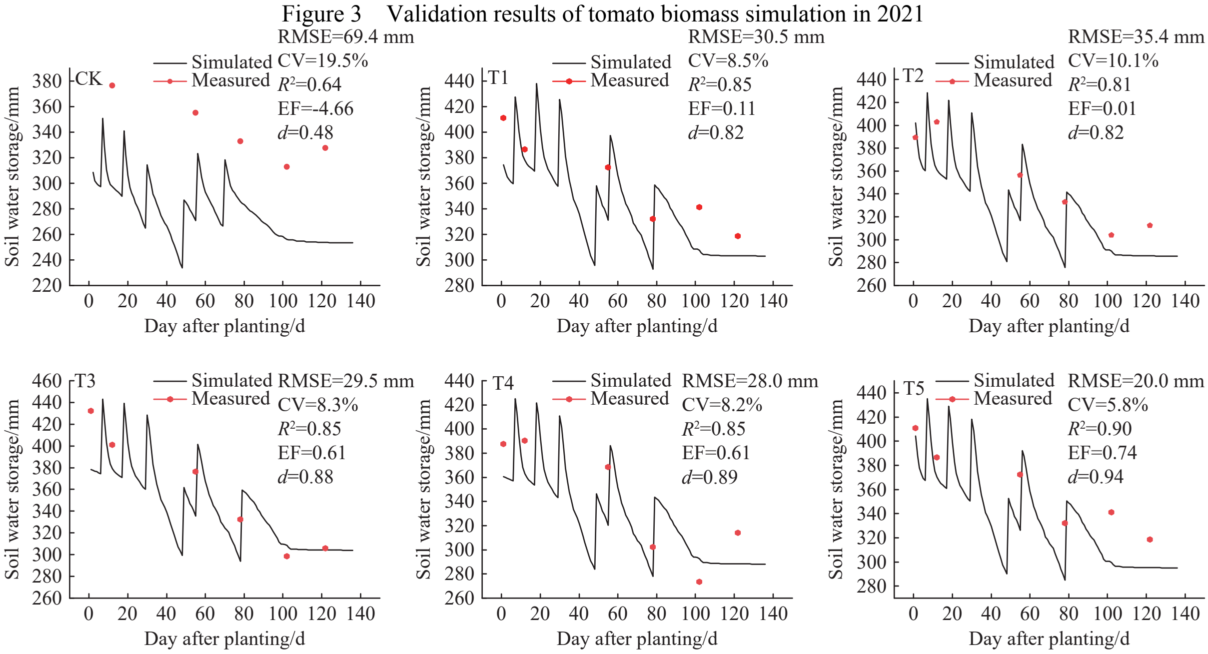


Figure 4 Validation results of volumetric soil water contents in the tomato root zone in 2021

3.1.4 Yield

The model calibration and verification results of tomato yield and biomass are presented in Table 3. The relative error of the simulated tomato yield ranged from 1.01% to 2.83%, while for biomass it ranged from 6.55% to 20.15%. The CK plot showed higher error in the simulated tomato yield and biomass. With the exception of the CK plot, the AquaCrop model demonstrated effective simulation of tomato yield and biomass under various irrigation scenarios.

Table 3 Calibration results of the tomato yield and biomass

Treatment	Final yield			Final mass		
	Model simulation value/ t·hm^{-2}	Field observations/ t·hm^{-2}	Pe/%	Model simulation value/ t·hm^{-2}	Field observations/ t·hm^{-2}	Pe/%
CK	8.430	8.198	2.83	14.872	12.378	20.149
T1	8.897	8.989	1.02	13.270	14.252	6.890
T2	8.787	8.632	1.80	13.105	14.024	6.553
T3	8.773	8.616	1.82	13.085	14.024	6.696
T4	8.698	8.524	2.04	12.978	11.957	8.539
T5	8.759	8.671	1.01	13.056	14.252	8.392

Note: Pe is the relative error.

3.2 Effects of different agricultural waste materials on tomato quality

The impact of various agricultural waste materials on tomato quality indicators such as hardness, soluble solids, soluble sugar, titratable acid, and sugar-acid ratio was examined. Table 4illustrates significant differences in tomato quality among treatments T1, T2, T3, T4, and T5 compared to the standard CK measures. Treatment T5 showed notable increases of 3.8% in hardness, 38.5% in soluble solids, 89.2% in soluble sugar, and 124.0% in sugar-acid ratio compared to CK. Treatment T1 exhibited a 1.6% increase in hardness, 22.1% in soluble sugar, and 35.3% in sugar-acid ratio, while soluble solids decreased by 10.8% compared to CK. Overall, T5 had the highest hardness (1.90 kg·cm^{2}·10^{5} Pa), T4 had the highest content of soluble solids (7.83%) and soluble sugar (3.19%), and T3 had the highest titratable acid content (0.81%).

3.3 Scenario simulation results

The study utilized the AquaCrop model to simulate tomato yield values, alongside calculating the associated water and fertilizer use efficiency. By considering varying proportions of agricultural wastes as the independent variables, regression analysis was conducted to establish a two-factor regression equation. Figure 5 illustrates the correlation between different agricultural wastes and the simulated yield, WUE, PFP, and sugar-acid ratio of tomatoes.

Table 4 Effects of different agricultural waste materials on tomato quality

Treatments	Hardness/ kg·cm^{2}·10^{5} Pa	Dissolved solid/%	Soluble sugar/%	Titratable acid/%	Sugar-acid ratio
T1	1.86^{a}	5.02^{d}	1.82^{c}	0.66^{b}	2.76^{c}
T2	1.61^{b}	7.17^{b}	2.72^{b}	0.60^{b}	4.51^{a}
T3	1.67^{b}	7.42^{b}	3.25^{a}	0.81^{a}	4.00^{b}
T4	1.63^{b}	7.83^{a}	3.19^{a}	0.66^{b}	4.82^{a}
T5	1.90^{a}	7.80^{a}	2.82^{b}	0.62^{b}	4.57^{a}
CK	1.83^{a}	5.63^{c}	1.49^{c}	0.75^{a}	2.04^{d}

As demonstrated inFigure 5, the proportions of organic fertilizer and distillers grains had a significant impact on simulated yield, water use efficiency, partial factor productivity of fertilizer, and sugar-acid ratio (p<0.05). Across various treatments with the same water and fertilizer inputs, there were notable differences in performance across the different indices. To determine the most suitable substrate ratios for tomatoes, this study utilized substrate ratios as independent variables and simulated yield, biomass, water use efficiency, and partial factor productivity of fertilizer as dependent variables for regression analysis. Two-factor regression equations Equations (8)-(11) were developed, and the NSGA-II algorithm was applied to find the optimal Pareto solution, thus identifying the optimal substrate ratio.

$$Y1 = 8.949 - 0.0124X_1^2 - 0.033X_2^2 - 0.0358X_1X_2 \quad (8)$$

$$Y2 = 2.3 + 0.0052X_1^2 + 0.0249X_2^2 + 0.0238X_1X_2 \quad (9)$$

$$Y3 = 2.0387 + 0.0046X_1^2 + 0.0221X_2^2 + 0.0211X_1X_2 \quad (10)$$

$$Y4 = 2.04 + 0.156X_1^2 + 0.0.578X_2^2 + 0.4045X_1X_2 \quad (11)$$

where Y1, Y2, Y3, and Y4 are the simulated tomato yield (t/hm²), WUE (kg/m³), PFP (kg/kg), and sugar-acid ratio, respectively. Meanwhile, X_1 and X_2 indicate the proportions of organic fertilization application and distillers grains, respectively.

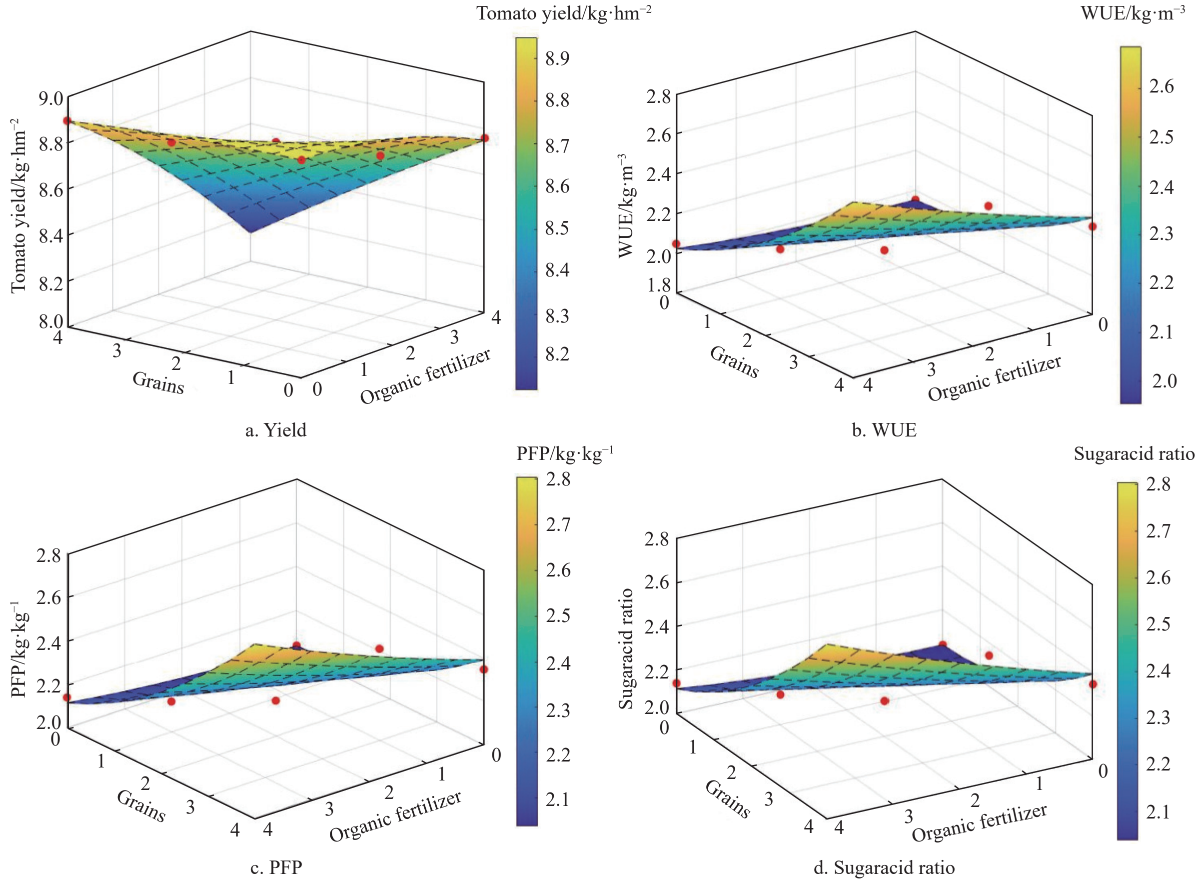


Figure 5 Regression relationship between different agricultural wastes and simulated tomato yield, water use efficiency, fertilizer partial productivity, and sugar-acid ratio

The multi-objective optimization model was established using the equations provided. The upper and lower limit values for organic fertilizer were designated as T1 and T5 treatments, respectively, while the upper and lower limit values for distiller grains were designated as T5 and T1 treatments, respectively. The NSGA-II algorithm was implemented using MATLAB 2020b. Parameters such as population size, mutation density, crossover probability, mutation probability, and maximum genetic algebra weresetat100,0.002,0.7,0.1,and600,respectively.Theoptimalyieldwas 8.79 t/hm², optimal WUE was 2.105 kg/m³, optimal PFP was 2.375 kg/kg, and optimal sugar-acid ratio was 4.17. The results indicated that the optimal treatment scenario for agricultural waste materials to achieve the Pareto solution was T5.

4 Discussion

4.1 Applicability of the AquaCrop model

The calibrated AquaCrop model using the tomato planting data from 2020 demonstrated accurate simulations of volumetric soil water content, canopy cover, biomass, and tomato crop yield. The simulation errors fell within acceptable ranges, aligning with previous studies utilizing the AquaCrop model. Notably, canopy cover simulations performed well across various crops[25-27]. Lu et al.[28]introduced a method involving Monte Carlo simulation to determine planting dates and quasi-calibrated phenological parameters, enhancing the AquaCrop model's ability to estimate maize yield. The study showed slight improvements in RMSE values for simulated yield and biomass data post-calibration. While the model tends to overestimate volumetric soil water content at initial stages, the prediction errors remain minimal[29,30], consistent with existing literature. Zhu et al.[31] also reported consistent results between simulated and measured aboveground biomass and yield values. Overall, this study underscores the AquaCrop model's effectiveness in simulating volumetric soil water content, tomato growth, and yield under different scenarios, accurately predicting changes in soil water content and tomato crop outcomes.

4.2 Determination of the optimal agricultural waste materials

Agricultural waste materials cultivation technology not only enhances the efficient utilization of agricultural waste resources but also saves water and fertilizer while ensuring good crop yield. Numerous researchers worldwide have demonstrated the effectiveness of agricultural waste material cultivation techniques in enhancing yields, water and fertilizer use efficiency, and the quality of lettuce, garlic, cucumber, and tomato[13,32-34]. However, Palencia et al.[35] found small differences in fruit yield under different agricultural waste materials (such as agricultural textiles, coconut shell fiber, perlite, and rock wool) without affecting fruit growth and quality, which contrasts with the results observed in this study. This discrepancy in the findings may be attributed to the absence of nutrient materials in Palencia's agricultural waste materials. Yang et al.[36]discovered that compound agricultural waste materials can effectively increase plant height, leaf area, root area, yield, and other morphological traits, consistent with the results reported in this study. The enhancement of morphological traits may be due to the application of distiller grains, which improve soil physical properties, increase soil organic matter, and ensure the slow release of nutrients necessary for crop growth.

This research investigated the suitability of the AquaCrop model in various input ratio scenarios. The findings suggest that this model is a valuable tool for studying the utilization of agricultural waste and the production of high-quality fruits and vegetables. By varying the proportions of different agricultural wastes in simulation scenarios, valuable insights were gained for the cultivation of premium tomatoes. The cultivation techniques using agricultural waste materials not only promote environmentally friendly agricultural practices and improve crop production but also contribute to the efficient utilization of agricultural waste resources, prevention of non-point source pollution in agriculture, and reduction of carbon emissions. Substrates composed of diverse agricultural waste materials offer a cost-effective solution for growing high-quality tomatoes, requiring less material compared to conventional modified substrates. Furthermore, the potential use of large quantities of agricultural waste in establishing solar photovoltaic conservation agricultural waste material farms could revolutionize the cultivation of premium fruits and vegetables while supporting traditional agriculture practices in the future.

5 Conclusions

In this study, the AquaCrop model was used to calibrate and validate crop growth parameters using tomato planting data from 2020 and 2021, under different agricultural waste materials. The validation results indicated that the AquaCrop model reasonably simulated canopy cover, biomass, and soil water content of the tomato crop. The R^2 values for soil water content simulation ranged from 0.63 in the CK plot to over 0.8 in other treatment scenarios.

By integrating the AquaCrop model with multi-objective optimization, an optimization model was developed to maximize tomato yield, WUE, PFP, and sugar-acid ratio. The NSGA-II algorithm was employed to find the optimal Pareto solution. The results suggested that agricultural waste materials T5 (loessial soil: straw: grains in a ratio of 5:1:4) could provide high yield, WUE, and PFP, with an optimal tomato yield of 8.79 t/hm^2 and WUE of 2.015 kg/m^3.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 52379042), Key R & D plan of Gansu Province (Grant No. 23YFFA0019), and Gansu Province East-West Cooperation Project (Grant No. 23CXNA0025).

[References]

[1] Lu Q M, Yan D, Wu P W, Chen L, Yagoub A E A, Ji Q H, et al. Ultrasound-NATDES/DMSO system for corn straw biomass conversion into platform compounds. Renewable Energy, 2022; 190: 675–683.

[2] Zhan X Y, Zhang A P, Zhang Q W. Controlling agricultural non-point source pollution: Thinking and practice in the era of agricultural green high-quality development. Transactions of the CSAE, 2020; 36(20): 1–7. (in Chinese)

[3] Joseph S, Kammann C I, Shepherd J G, Conte P, Schmidt H-P, Hagemann N, et al. Microstructural and associated chemical changes during the composting of a high temperature biochar: mechanisms for nitrate, phosphate and other nutrient retention and release. Science of the Total Environment, 2018; 618: 1210–1223.

[4] Dadrasnia A, de Bona Muñoz I, Yáñez E H, Lamkaddam I U, Mora M, Ponsá S, et al. Sustainable nutrient recovery from animal manure: A review of current best practice technology and the potential for freeze concentration. Journal of Cleaner Production, 2021; 315: 128106.

[5] Jatav H S, Rajput V D, Minkina T, Singh S K, Chejara S, Gorovtsov A, et al. Sustainable approach and safe use of biochar and its possible consequences. Sustainability, 2021; 13(18): 10362.

[6] Gustavo Adolfo F-G, Wolf-Anno B, Martin R, Christina S. Co-composting of biochar and nitrogen-poor organic residues: Nitrogen losses and fate of polycyclic aromatic hydrocarbons. Waste Management, 2022; 143: 84–94.

[7] Zhao W J, Ji H, Wang Z J, Fan Y W, Liu Y H. Resisting drought and promoting root ecological raising module and manufacturing method, 2021. AU 2020104391.

[8] Steduto P, Hsiao T C, Raes D, Fereres E. AquaCrop—The FAO crop model to simulate yield response to water: I. Concepts and underlying principles. Agronomy Journal, 2009; 101(3): 426–437.

[9] Raes D, Steduto P, Hsiao T C, Fereres E. AquaCrop—the FAO crop model to simulate yield response to water: II. Main algorithms and software description. Agronomy Journal, 2009; 101(3): 438–447.

[10] Du W Y, He X C, Shamaila Z, Hu Z F, Zeng A J, Muller J. Yield and biomass prediction testing of AquaCrop model for winter wheat. Transactions of the CSAM, 2011; 42(4): 174–174, 183.

[11] Katerji N, Campi P, Mastrorilli M. Productivity, evapotranspiration, and water use efficiency of corn and tomato crops simulated by AquaCrop under contrasting water stress conditions in the Mediterranean region. Agricultural Water Management, 2013; 130: 14–26.

[12] Linker R, Ioslovich I, Sylaios G, Plauborg F, Battilani A. Optimal model-based deficit irrigation scheduling using AquaCrop: A simulation study with cotton, potato and tomato. Agricultural Water Management, 2016; 163: 236–243.

[13] Xu J, Jia K, Zhu J F, Hu M, Wang N, Gao J. Combined application of nitrogen and sulfur improving quality of substrate culture garlic bulbs. Transactions of the CSAE, 2017; 33(4): 203–208. (in Chinese)

[14] Guo D X, Zhao R H, Xing X G, Ma X Y. Global sensitivity and uncertainty analysis of the AquaCrop model for maize under different irrigation and fertilizer management conditions. Archives of Agronomy and Soil Science, 2020; 66(8): 1115–1133.

[15] Linker R, Ioslovich I. Assimilation of canopy cover and biomass measurements in the crop model AquaCrop. Biosystems Engineering, 2017; 162: 57–66.

[16] Zhang J P, Li K J, Gao Y, Feng D, Zheng C L, Cao C Y, et al. Evaluation of saline water irrigation on cotton growth and yield using the AquaCrop crop simulation model. Agricultural Water Management, 2022; 261: 107355.

[17] Shao D G, Le Z H, Xu B L, Hu N J, Tian Y N. Optimization of irrigation scheduling for organic rice based on AquaCrop. Transactions of the CSAE, 2018; 34(19): 114–122. (in Chinese)

[18] Ran H, Kang S Z, Li F S, Du T S, Tong L, Li S E, et al. Parameterization of the AquaCrop model for full and deficit irrigated maize for seed production in arid Northwest China. Agricultural Water Management, 2018; 203: 438–450.

[19] Dubey S K, Sharma D. Assessment of climate change impact on yield of major crops in the Banas River Basin, India. Science of the Total Environment, 2018; 635: 10–19.

[20] Song J, Li J, Yang Q H, Mao X M, Yang J, Wang K. Multi-objective optimization and its application on irrigation scheduling based on AquaCrop and NSGA-II. Journal of Hydraulic Engineering, 2018; 49(10): 1284–1295. (in Chinese)

[21] Nyathi M K, van Halsema G E, Annandale J G, Struik P C. Calibration and validation of the AquaCrop model for repeatedly harvested leafy vegetables grown under different irrigation regimes. Agricultural Water Management, 2018; 208: 107–119.

[22] Adeboye O B, Schultz B, Adekalu K O, Prasad K C. Performance evaluation of AquaCrop in simulating soil water storage, yield, and water productivity of rainfed soybeans (*Glycine max* L. merr) in Ile-Ife, Nigeria. Agricultural Water Management, 2019; 213: 1130–1146.

[23] Takács S, Csengeri E, Pék Z, BíróT, Szuvandzsiev P, Palotás G, et al. Performance evaluation of aquacrop model in processing tomato biomass, fruit yield and water stress indicator modelling. Water, 2021; 13(24): 3587.

[24] Zhao W J, Ma F, Cao W, Ma F F, Han L. Effects of water and fertilizer coupling on the yield and quality of tomatoes. Transactions of the CSAE, 2022; 38(2): 95–101.

[25] Amiri E. Calibration and testing of the Aquacrop model for rice under water and nitrogen management. Communications in Soil Science and Plant Analysis, 2016; 47(3): 387–403.

[26] Bello Z A, Walker S. Evaluating AquaCrop model for simulating production of amaranthus (*Amaranthus cruentus*) a leafy vegetable, under irrigation and rainfed conditions. Agricultural and Forest Meteorology, 2017; 247: 300–310.

[27] Malik A, Shakir A S, Ajmal M, Khan M J, Khan T A. Assessment of AquaCrop model in simulating sugar beet canopy cover, biomass and root yield under different irrigation and field management practices in semi-arid regions of Pakistan. Water Resources Management, 2017; 31(13): 4275–4292.

[28] Lu Y, Wei C Z, McCabe M F, Sheffield J. Multi-variable assimilation into a modified AquaCrop model for improved maize simulation without management or crop phenology information. Agricultural Water Management, 2022; 266: 107576.

[29] Zeleke K T, Luckett D, Cowley R. Calibration and testing of the FAO AquaCrop model for canola. Agronomy Journal, 2011; 103(6): 1610–1618.

[30] Iqbal M A, Shen Y J, Stricevic R, Pei H W, Sun H Y, Amiri E, et al. Evaluation of the FAO AquaCrop model for winter wheat on the North China Plain under deficit irrigation from field experiment to regional yield simulation. Agricultural Water Management, 2014; 135: 61–72.

[31] Xu K, Zhu X F, Liu Y, Hou C Y. Vulnerability of drought disaster of maize in China based on AquaCrop model. Transactions of the CSAE, 2020; 36(1): 154–161. (in Chinese)

[32] Liu Z G, Wang J Z, Xu Y F, Li P P. Lettuce yield and root distribution in substrates under drip irrigation and micro-sprinkler irrigation. Transactions of the CSAM, 2014; 45(2): 156–160. (in Chinese)

[33] Li Y L, Guo W Z, Zhao Q, Li Y K, Yang Z Q, Xue X Z. Irrigation scheduling based on moisture and electric conductivity sensors in organic culture of cucumber. Transactions of the CSAM, 2017; 48(6): 263–270. (in Chinese)

[34] Xiong J, Chen Q, Wang J G, Liu W. Effect of culture systems on salt accumulation in substrate and nutrient use efficiency of tomato. Transactions of the CSAM, 2017; 48(2): 224–231.

[35] Palencia P, Bordonaba J G, Martínez F, Terry L A. Investigating the effect of different soilless substrates on strawberry productivity and fruit composition. Scientia Horticulturae, 2016; 203: 12–19.

[36] Yang Y, Ni X Y, Zhou Z J, Yu L X, Liu B M, Yang Y, et al. Performance of matrix-based slow-release urea in reducing nitrogen loss and improving maize yields and profits. Field Crops Research, 2017; 212: 73–81.