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RESEARCH ARTICLE

Comparing simulated and observed cotton transpiration in relation to climatic factors

Zeshan Zhang[1], Pengzhong Zhang[5#], Yongfan Chen[1], Xuejiao Wang[2], Mingfeng Yang[3], Shuai Sun[4], Yutong Zhang[1], Sen Wang[2], Fen Ji[3], Chunrong Ji[2], Dao Xiang[3], Parhat Mamat[5], Lizhen Zhang[1, 5#]

[1] *Agricultural Meteorology Department, College of Resources and Environmental Sciences, China Agricultural University, Beijing 100193, China*
[2] *Xinjiang Agrometeorological Observatory, Urumqi 830002, China*
[3] *Wulanwusu Agrometeorological Station, Shihezi 832199, China*
[4] *Institute of Desert Meteorology, China Meteorological Administration, Urumqi 830002, China*
[5] *China National Cotton R&D Center, Xinjiang Academy of Agricultural Sciences, Urumqi 830091, China*

Highlights

- The estimated transpiration of the AquaCrop Model was slightly higher than that of sap flow measurements.
- The model could capture the trends of transpiration with climatic factors, but it responded stronger than sap flow observations.
- The daily transpiration was overestimated due to the overweighting of canopy cover and crop coefficients.

Abstract

Water-driven crop simulation models are often employed to evaluate crop yields and irrigation management strategies for improving agricultural water productivity. Well-tested models can serve as powerful tools for guiding agricultural practices. The objective of this study was to assess the capability of the AquaCrop Model for simulating cotton transpiration and water use under drip irrigation conditions compared with field sap flow measurements. A two-year field experiment (2020–2021) in cotton was conducted in Xinjiang, China, including two row spacings and two topping methods. The model adequately estimated canopy cover with a normalized root mean square error (nRMSE) of less than 5% and a model efficiency (EF) close to 1. The model estimation of transpiration showed good agreement with sap flow measurements (nRMSE=22.4%) across all years and treatments. The model simulated water use efficiency (WUE) values for cotton (4.42 g m^{-2} mm^{-1}) were lower than those calculated from actual measurements with WUE of 4.79 g m^{-2} mm^{-1}. The estimated transpiration was slightly higher than that measured using a sap flow meter due to an 11.5% overestimation of the crop coefficient in the model when cotton grew in a short and dense canopy structure under drip irrigation and plastic film cover conditions. Air temperature, vapor pressure difference and radiation had positive effects on cotton transpiration while humidity had negative effects. The model could capture the trends of transpiration with climatic factors, but the climatic effects were stronger than those of the sap flow observation. In conclusion, the AquaCrop Model is a useful tool for optimizing cotton irrigation strategies.

Keywords: AquaCrop, machine-harvested cotton, sap velocity, chemical topping, row spacing, evapotranspiration.

1. Introduction

Water is considered the most critical development factor for future crop production (Weinzettel and Pfister 2019). As the population grows, urban and industrial water demand increases, so there is pressure on the availability of water for agriculture (Feike and Henseler 2017). Water scarcity limits the productivity of agricultural systems, and climate change may exacerbate uncertainty in the water supply. The rational utilization of water resources and improvement of water productivity are crucial for sustainable agriculture (Yu *et al.*

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Zeshan Zhang, E-mail: zhangzeshan@cau.edu.cn; #Correspondence Lizhen Zhang, E-mail: zhanglizhen@cau.edu.cn; Pengzhong Zhang, E-mail: zhangpz@163.com

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2021).

The arid region of Xinjiang, located in northwestern China, faces severe water shortages due to high evaporation and low precipitation (Guo and Shen 2016). Most agricultural water in Xinjiang is not from precipitation but from irrigation that uses surface water originating from snowmelt in mountain ranges such as the Tianshan. With regional economic development and agricultural expansion, the supply and allocation of water resources have become key issues in this region (Wang *et al.* 2021). Cotton is the most widely planted crop in Xinjiang with high yields and profits. In this region, cotton is grown at high density and irrigated using drip systems under plastic film (Ning *et al.* 2015). For mechanical harvesting, the ideal planting row spacing for cotton in Xinjiang is either narrow–wide (10+66 cm) or equal (76 cm) row spacing, which are the common practices among local farmers (Feng *et al.* 2024). The crucial practice of topping for removing apical dominance and regulating plant growth (Dai *et al.* 2022) has progressively transitioned from manual methods to chemical techniques in recent years due to labor shortages. During the growing season, water is the most important factor limiting cotton production.

Proper irrigation is essential for avoiding water stress and achieving maximum crop yield, but it requires an understanding of the cotton's water consumption across different scenarios (Rajan *et al.* 2010; Akhtar *et al.* 2013). Row spacing, whether equal or narrow–wide, affects canopy light interception and interplant water competition (Zuo *et al.* 2024), thereby influencing cotton transpiration. With its higher density and leaf area index, narrow–wide row planting may result in greater water consumption (Gao *et al.* 2024). In addition, different topping methods can modify cotton photosynthesis and the allocation of assimilates, which in turn impacts water use efficiency (WUE) (Nie *et al.* 2021). Field experiments to assess crop water use under varying management practices are often costly and challenging to conduct on a large scale. In this context, crop models offer a practical and cost-effective alternative. These models can be employed to predict field evapotranspiration, optimize irrigation schedules, and improve crop water productivity under various environmental and management conditions (Toumi *et al.* 2016).

The Food and Agriculture Organization of the United Nations (FAO) has developed the AquaCrop Model for assessing crop water use and productivity across varying environments and management practices (Steduto *et al.* 2009). AquaCrop inputs include climatic data, crop characteristics, field management practices, and soil files. In the model, crops grow and develop on a daily time step by forming green canopies (Andarzian *et al.* 2011; Vanuytrecht *et al.* 2014). The AquaCrop Model uniquely separates evapotranspiration into independent calculations of transpiration and evaporation, enabling a more precise assessment of the actual water requirements of crops. Crop transpiration is calculated as the product of reference evapotranspiration (ET_o), canopy cover (CC), and the crop coefficient (Kc_{Tr}) (Sandhu and Irmak 2019). Meanwhile, soil evaporation is assessed by considering the fraction of soil surface that remains uncovered. This model has been parameterized and tested on crops like maize, wheat and cotton (Farahani *et al.* 2009; Masanganise *et al.* 2012). It can simulate the green CC, soil water content, crop transpiration, and crop yield under fully irrigated and adequate fertility conditions (Linker and Ioslovich 2017). When using plastic mulch and drip irrigation, soil evaporation is significantly reduced, and most of the water is allocated to crop transpiration. The AquaCrop Model, which calculates transpiration based on CC, may offer advantages in such conditions. Li *et al.* (2024) used the AquaCrop Model for simulations and found that under the influence of climate change, the WUE and potential yield of cotton increased, while actual evapotranspiration decreased. However, the results were uncertain due to the lack of measured transpiration data for parameter calibration. Therefore, despite the potential of AquaCrop, its ability to accurately simulate transpiration under the local conditions of Xinjiang has not been validated. A thorough validation of the performance of AquaCrop for cotton in Xinjiang is essential for determining whether this model can be reliably employed to optimize irrigation practices in the region. Because determining crop transpiration under field conditions is difficult, few studies have evaluated the accuracy of simulated transpiration directly (Ran *et al.* 2017; Li *et al.* 2019).

Transpiration is the process of water loss from the stomata of plant leaves, and the conservation of mass is equal to the sap flow of the xylem at the base of the plant stem (Ellison *et al.* 2012). By applying heat to the crop stem and calculating sap flow velocity using the temperature ratio, continuous measurements of plant water use can be obtained (Marshall 1958). The sap flow method has been widely used to quantify water consumption in trees and stands (Poyatos *et al.* 2016), and it has also been applied to transpiration studies of thin-stemmed woody plants and herbaceous species (Clearwater *et al.* 2009). Recently, it has been validated and employed in field crops such as wheat (Cai *et al.* 2018; Rafi *et al.* 2019), maize (Tolk *et al.* 1995; Capurro *et al.* 2024), tomato (De Swaef *et al.* 2013), and soybean (Gao *et al.* 2013). The results can be scaled up to estimate canopy transpiration or to partition evapotranspiration into the soil and plant components (Miner *et al.* 2017). Among the methods for determining sap flow, the heat ratio method (HRM) has the advantage of a fast response time and small error when the amount of crop stem water variation is relatively small (Bleby *et al.* 2004; Fuchs *et al.* 2017). This method has been successfully used to determine the crop transpiration and WUE of cotton, with transpiration and water potential showing reasonable consistency (Chen *et al.* 2022, 2024). Therefore, a simulation model such as AquaCrop can be validated by direct measurements of crop transpiration under field conditions to provide helpful information for improving the model performance.

The objectives of this study were: (1) to assess the performance of the AquaCrop Model in simulating cotton transpiration under drip irrigation with film mulching, in the context of the varying agronomic management practices in Xinjiang; and (2) to explore the limitations of the model parameters (e.g., Kc_{Tr}) for further improving the model.

2. Materials and methods

2.1. Field experiment

A field experiment was conducted from 2020 to 2021 at the Wulanwusu Agrometeorology Experiment Station in Xinjiang, China (44°17′N, 85°49′E). The site has a temperate continental climate and reclaimed sandy loam soil that is not subject to saline stress. The underground water table is deeper than 6 m, and runoff can be considered negligible. The average annual total precipitation was 76 mm, and the annual mean temperature was 19.4°C during the cotton growing season (April to October) on average in 2020 and 2021. The soil bulk density was 1.41 g cm^{-3}, with a field capacity of 0.28 m^3 m^{-3}. The soil organic matter content within the 0–20 cm layer was 17 g kg^{-1}, along with 0.91 g kg^{-1} for total nitrogen, 91.5 mg kg^{-1} for available phosphorus, and 315 mg kg^{-1} for available potassium. Meteorological data were collected every half hour by an automatic weather station (SNiP-AWS5+, ICT International, Armidale, Australia), placed on a flat, unobstructed surface 30 m away from the experimental site. The data for 2020 to 2021 are shown in Fig. 1.

The experiment had four experimental treatments based on combining two methods for top removal or suppression ("topping"), a measure used in cotton to break apical dominance and enhance boll growth while curtailing vegetative growth, and two row spacings of cotton: equal row spacing and narrow–wide row spacing. The chemical-topping treatment applied a heavy amount (225 g ha^{-1}) mepiquat chloride to terminate the growth of the main stem bud, while manual topping was done by cutting the top bud by hand. Both equal row spacing (76 cm wide, 18 plants m^{-2}) and narrow–wide row spacing (10 and 66 cm, 15 plants m^{-2}) included strip widths of 2.28 m. The cotton cultivar used was Xinluzao 78, which is extensively cultivated in northern

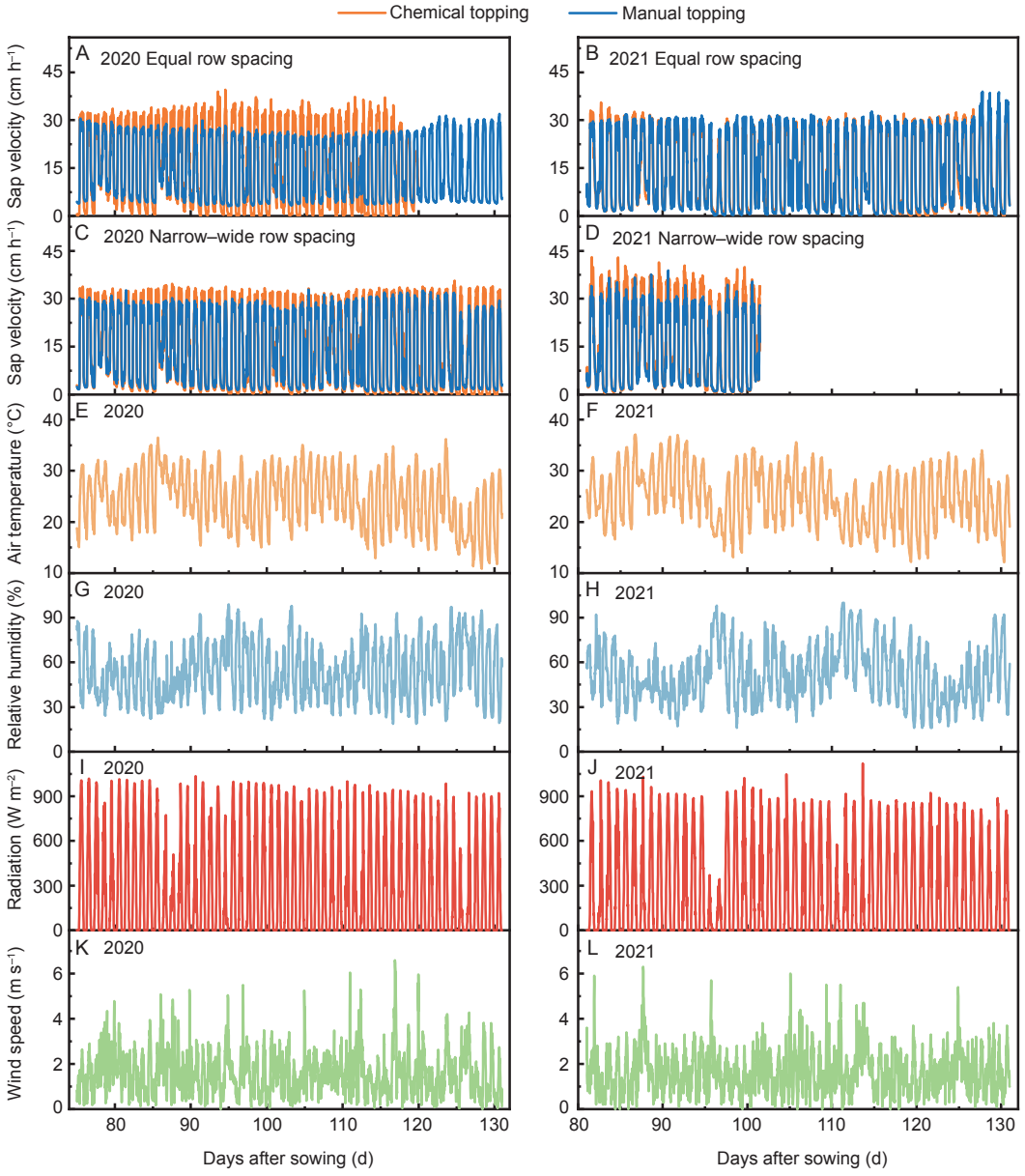


Fig. 1 Weather data at the experimental site and sap flow of cotton in 2020 and 2021.

Xinjiang. The seeds were sown on 24 April 2020 and 27 April 2021 in north–south rows, and the cotton was harvested in October. Each replicate was contained in a rectangular plot 4.5 m wide and 7 m long, and the soil surface was covered with synthetic plastic mulches achieving 87% coverage. Crop water demand was met by drip irrigation using three belts located under the plastic film, which provided an average of 417 mm of water per year. Irrigation was applied seven times in 2020 and eight times in 2021, with each irrigation event not exceeding 65 mm and irrigation intervals ranging from 10 to 16 days. A water-soluble compound fertilizer was applied through the drip irrigation system to deliver nutrients along with the irrigation water. To ensure adequate nutrition, soil nutrients were measured and sufficient fertilizer was applied. Annually, nitrogen (N) was applied at 680 kg ha^{-1}, phosphorus (P) at 270 kg ha^{-1}, and potassium (K) at 80 kg ha^{-1}. Timely pesticide spraying was done to control pests and weeds, ensuring that the cotton crop was not subjected to nutrient or pest stresses.

2.2. Sap flow and transpiration measurements

Sap flow in the cotton plants was quantified using sap flow meters (SFM, ICT International, Armidale, Australia) from August to October during both 2020 and 2021. To scale up from transpiration per plant to transpiration per unit ground area, 12 plants per plot was randomly selected to measure stem diameter (first internode), and then one of plants in each treatment had a sap flow meter installed. The SFM instrument features a central heating probe and thermal probes on either side, each with a diameter of 1.25 mm. The positioning plate was placed parallel to the main stem near the cotyledon node of the cotton plants, and the SFM was inserted using a micro hand drill. To minimize the impact of direct solar radiation and ambient temperature on the measurements, the probe was wrapped in tin foil. The SFM was powered by solar panels and recorded sap flow data every half hour.

The sap flow meter operated on the heat ratio method (HRM), utilizing a heat source as a tracer. A heating probe was inserted into the plant stem, and the thermal probes were installed at the top and bottom 5 mm of the heating probe. The heating probe was charged for 3–5 s to release the thermal pulse, and the temperature changes upstream and downstream were measured to calculate the heat pulse velocity (V_h, cm h^{-1}) by the heat transfer ratio. The calculation of V_h was based on the following formula:

$$V_h=\frac{k}{x}\ln\left(\frac{T_1}{T_2}\right)\times 3{,}600 \quad (1)$$

where k is the thermal diffusivity of fresh woody plants, which was given a nominal value of 0.0025 cm^2 s^{-1}; x is the interval between the probes inserted into the plant stem, fixed at 0.5 cm; and T_1 and T_2 are the temperatures of the top and bottom thermal probes, respectively.

Installation of the sensor probe can cause mechanical damage to the crop stem leading to compromised V_h measurements. To account for this, the V_h was corrected using the wound correction algebraic equation and correction factor:

$$V_c=bV_h+cV_h^2+dV_h^3 \quad (2)$$

where V_c (cm h^{-1}) is the corrected heat pulse velocity; b, c and d are wound calibration coefficients for the sap flow meter, with values of 1.6821, –0.0015, and 0.0002, respectively (Burgess *et al.* 2001).

The heartwood of woody plants typically appears after two years of crop growth, whereas the annual crop cotton is too short lived to produce significant heartwood, so its sap flow area is almost equal to the cross-sectional area of the stem. Therefore, the sap flow velocity in cotton was determined by measuring the xylem water content, density and specific heat capacity. The calculation of sap flow velocity in cotton was based on the following formula:

$$V_s=V_c\cdot\frac{\rho_b\cdot(c_w+m_c\cdot c_s)}{\rho_s\cdot c_s} \quad (3)$$

where V_s (cm h^{-1}) is the corrected sap velocity based on heat pulse velocity; ρ_b (0.5 g cm^{-3}) is the basic density of sapwood calculated from dry weight and fresh volume; ρ_s (1 g cm^{-3}) is the basic density of water; c_w (1,200 J kg^{-1} °C^{-1}) is the specific heat capacity of wood; c_s (4,182 J kg^{-1} °C^{-1}) is the specific heat capacity of water; and m_c is the moisture content of sapwood, fixed at 1.

The calculation eqs. (1), (2), and (3) are integrated within the sap flow meter, allowing the user to simply adjust the default thermal diffusivity, wounding coefficient, basic density of sapwood, and sapwood area parameters in the ICT software. The instrument then directly outputs the calculated and corrected V_s (cm h^{-1}).

The daily transpiration of individual plants was determined based on the entire sap area of the stem and the sap flow velocity per day. The canopy transpiration (T_r) was derived from the transpiration of a sample plant and plant population density (Chen *et al.* 2022, 2024).

$$T_r=\overline{V}_s\times 3.14\times(D/2)^2\times PPD\times 24\times 10^{-3} \quad (4)$$

where T_r (mm d^{-1}) is cotton transpiration per unit area, $\overline{V}_s$ (cm h^{-1}) is the daily averaged sap velocity of individual plants, D is the mean stem diameter of 12 plants measured in each plot used to calculate the sap area and PPD (plant m^{-2}) is the population density of the planted cotton.

2.3. Measurements of aboveground dry matter and leaf CC

The above-ground biomass of cotton was measured at least six times annually. Measurements were taken on days 28, 47, 68, 87, 109, and 123 after sowing in 2020, and on days 50, 60, 70, 90, 111, 121, and 132 after sowing in 2021. Three cotton samples were randomly selected from each plot at the sampling site. The cotton plants were segregated into leaves, petioles, stems, and fruits, and the samples were dried in an oven at a constant temperature of 80°C until they reached a constant weight.

During the final annual biomass assessment, concurrent measurements of cotton leaf size (length and width) were taken as they reached their maximum. The leaf area was calculated by multiplying the length, width, and a shape factor of 0.83 (Zhang *et al.* 2008). The leaf area index was calculated by determining the average total leaf area per plant and the plant density. The CC was estimated by using

the leaf area index as follows:

$$CC=1-e^{-k\cdot L} \quad (5)$$

where k represents the crop-specific extinction coefficient, which was 0.95 for cotton (Wu *et al.* 2023) in this study; and L is the leaf area index.

2.4. Water use efficiency

Water use efficiency (WUE, g m^{-2} mm^{-1}) is an essential parameter used to assess the effectiveness of irrigation scheduling decisions on water management. WUE characterizes the relationship between crop biomass production and the volume of water used in crop growth, and it is represented as the crop biomass produced per unit of water consumed:

$$WUE=\frac{B}{\sum T_r} \quad (6)$$

where WUE (g m^{-2} mm^{-1}) represents the water use efficiency calculated from biomass; and B (g m^{-2}) indicates the total above-ground dry matter.

2.5. Calculation of the crop coefficient using observations

The AquaCrop Model uses Kc_{Tr} that specifically represents plant transpiration to distinguish it from ET_o. The present study focused on the period from flowing to harvest, so the cotton CC was close to 1 and soil evaporation was largely diminished and close to zero. Therefore, the ET calculated by the model can be considered as plant transpiration (Tan *et al.* 2020). To evaluate the validity of Kc_{Tr} in the model, the Kc_{Tr} was calculated using the observed transpiration and ET_o.

$$Kc_{Tr}=T_r/ET_o \quad (7)$$

where ET_o (mm) was determined using the Penman-Monteith equation (Rotstayn *et al.* 2006).

2.6. Vapor pressure deficit

Vapor pressure deficit (VPD) is defined as the difference between the saturated vapor pressure and the actual vapor pressure of the air at any given moment. VPD significantly influences plant WUE while providing an essential measure of environmental dryness or humidity. It also serves as a critical metric for evaluating air humidity levels and predicting potential rates of evaporation and transpiration:

$$VPD=(1-RH)\times\frac{e^\circ(T_{max})+e^\circ(T_{min})}{2} \quad (8)$$

$$e^\circ(T)=0.6108\times\exp\left(\frac{17.27\times T}{T+237.3}\right) \quad (9)$$

where RH (%) is the relative humidity, $e^\circ(T_{max})$ represents the saturated vapor pressure corresponding to the daily maximum temperature, and $e^\circ(T_{min})$ represents the saturated vapor pressure at the daily minimum temperature.

2.7. Model parameterization

The AquaCrop Model allows users to modify input parameters in the climate, crop, management, and soil files. Canopy cover is a key feature of AquaCrop, as it simulates crop development, water use, and yield by controlling canopy changes. The initial canopy cover (CC_0) is determined by crop planting density, germination rate, and the initial canopy size of each seedling. Canopy growth and senescence are controlled by parameters such as the canopy growth coefficient (CGC), maximum canopy cover (CC_x), canopy decay coefficient (CDC), and specific phenological dates. The effect of temperature on crops is represented by the accumulated growing degree days (GDD) for each growth stage, calculated based on the base temperature (T_{base}) and upper threshold temperature (T_{upper}). Throughout the growing season, water storage in the root zone is simulated by accounting for water fluxes entering (from rainfall and irrigation) and exiting (through runoff, evapotranspiration, and deep percolation) the root zone. Water stress affects the progression of the CC by influencing stomatal conductance, leaf growth, and canopy attenuation, which are represented in the model through specific threshold parameters (P_{exp}, P_{sto}, and P_{sen}). In this study, the model parameters were calibrated based on the recommendations of the AquaCrop reference manual (Raes *et al.* 2009), which were adjusted based on field observations because of the special agronomic practices in Xinjiang (Table 1).

2.8. Statistical analysis

R 4.2.0 software was employed for experimental data processing and statistical analysis. The anova() function was used for multivariate analysis of variance, and the TukeyHSD() function was used for multiple comparisons. Origin 2021 was used for graphing the results. The current investigation employed several statistical measures for evaluating the degree of agreement between simulated and field-observed data. These measures included the normalized root mean square error (nRMSE), model efficiency (EF) and coefficient of residual mass (CRM), which can be expressed mathematically as follows:

$$nRMSE\ (\%)=\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i-S_i)^2}}{\bar{M}}\times 100 \quad (10)$$

$$EF=1-\frac{\sum_{i=1}^{n}(M_i-S_i)^2}{\sum_{i=1}^{n}(M_i-\bar{M})^2} \quad (11)$$

$$CRM=\frac{\sum_{i=1}^{n}M_i-\sum_{i=1}^{n}S_i}{\sum_{i=1}^{n}M_i} \quad (12)$$

where M_i and S_i denote the measured and simulated values; n represents the number of measurements; and $\bar{M}$ is the mean measured value. The nRMSE indicates the extent of agreement between simulated and observed data, with an nRMSE value approaching zero signifying excellent simulation. The EF measures the magnitude of the residual variance relative to that of the observations. A higher EF value that converges toward 1 signifies a superior match between the model and the measured data, while a zero or negative EF value indicates less effective use of the model. Lastly, the CRM measures the tendency of the model to either overestimate or underestimate the measurements, with positive and negative CRM values indicating underestimation and overestimation, respectively.

Table 1 Input parameters of AquaCrop

Input parameter	Description	Narrow–wide row spacing		Equal row spacing		Source
		Chemical topping	Manual topping	Chemical topping	Manual topping	
CC_0	Initial canopy cover (%)	1.30	1.30	1.0	1.0	Measured
CGC_{2020}	Canopy growth coefficient in 2020 (% d^{-1})	12.2	12.2	12.8	12.8	Measured
CC_{x2020}	Maximum canopy cover in 2020 (%)	92	91	93	91	Measured
CGC_{2021}	Canopy growth coefficient in 2021 (% d^{-1})	10.4	10.4	11.3	11.3	Measured
CC_{x2021}	Maximum canopy cover in 2021 (%)	99	98	99	99	Measured
CDC	Canopy decline coefficient (% d^{-1})	15.2	6.4	15.2	6.4	Measured
T_{base}	Base temperature (°C)	12	12	12	12	Recommended
T_{upper}	Upper temperature (°C)	35	35	35	35	Recommended
$Kc_{Tr,x}$	Crop coefficient for transpiration at CC=100% prior to senescence	1.1	1.1	1.1	1.1	Recommended
$P_{exp,\ upper}$	Upper threshold of soil water availability in the root zone when canopy expansion is limited	0.35	0.35	0.35	0.35	Measured
$P_{exp,\ lower}$	Soil water availability in the root zone when canopy expansion stops	0.70	0.70	0.70	0.70	Measured
P_{sto}	Soil water depletion upper threshold for stomatal control	0.35	0.35	0.35	0.35	Measured
P_{sen}	Soil water depletion upper threshold for canopy senescence	0.70	0.70	0.70	0.70	Measured

3. Results

3.1. Canopy cover

The CC for cotton at the emergence stage (CC_0, 7 days after sowning (DAS)) in narrow–wide row spacing was 0.75%, while it was 0.9% in equal row spacing. During the early growth stages, the CC curves for all treatments followed similar patterns. After 70 DAS, the CC reached its maximum (CC_x), with only slight differences in CC_x among the treatments (91–99%). The use of defoliants in the chemical topping treatment increased the canopy decline coefficient by 8.8% compared to the manual topping treatment (Fig. 2; Table 2). The model accurately simulated the developmental trend of CC, with an average normalized root mean square error (nRMSE) of 3.15% across all years and treatments, with EF of 0.96 and CMR of 0.01.

3.2. Simulated and measured transpiration

Cotton transpiration was more pronounced under the chemical topping and equal row-spacing treatments (Fig. 3). The measured transpiration of cotton between 75 and 130 days after sowing averaged 4.40 mm d^{-1} across all years and treatments, which was 11.1% lower than simulated value (4.82 mm d^{-1}) (Table 3). Overall, the prediction error for cotton transpiration between the model simulations and observations was larger in narrow–wide row spacing (nRMSE=18.66%, EF=–0.50, CMR=–0.03) than in equal row spacing (nRMSE=26.04%, EF=–1.64, CMR=–0.19), indicating a better model estimation in the homogeneous canopy (Fig. 4).

3.3. Water use efficiency

The AquaCrop Model tended to overestimate the actual transpiration of cotton and to underestimate the WUE, with notable differences between the simulated and measured values (Table 3). In 2020, the measured WUE values for equal row spacing were higher than those for narrow–wide row spacing, with a maximum WUE of 5.2 g m^{-2} mm^{-1}. The chemical topping treatments were more effective than the manual topping treatments, and the model simulations showed similar trends. In 2021, the transpiration data for the narrow–wide row spacing treatments were lost due to instrument failure. However, based on the results of the equal row spacing treatments, the WUE of the chemical topping treatment (4.60 g m^{-2} mm^{-1}) remained higher than that of the manual topping treatment (4.44 g m^{-2} mm^{-1}) in 2021.

3.4. Responses to climatic factors

Transpiration showed an increasing trend, but it reached a maximum value when the air temperature was above a certain threshold, which differed between years and row spacings, at around 20°C in 2020 and 25°C in 2021 for narrow–wide row spacing, but around 24°C for equal row spacing in both years. The transpiration decreased when relative humidity was higher than around 60%. The transpiration increased with radiation intensity, however, it showed no change when the radiation exceeded around 250 W m^{-2}. The vapor pressure deficit (VPD) showed a similar pattern with air temperature (Fig. 5).

The linear relationship between transpiration and climatic factors for model simulations and field observations showed the same general trend but with some differences. Model simulations showed stronger responses to air temperature and radiation than the observations (Fig. 6).

3.5. Crop coefficient

Kc_{Tr} estimated by model simulated transpiration and ET_o decreased slightly and linearly after 80 days after sowing, while the calculated Kc_{Tr} using field measured transpiration varied daily (Fig. 7). The Kc_{Tr} was higher in equal row spacing than in narrow–wide row spacing, and also higher

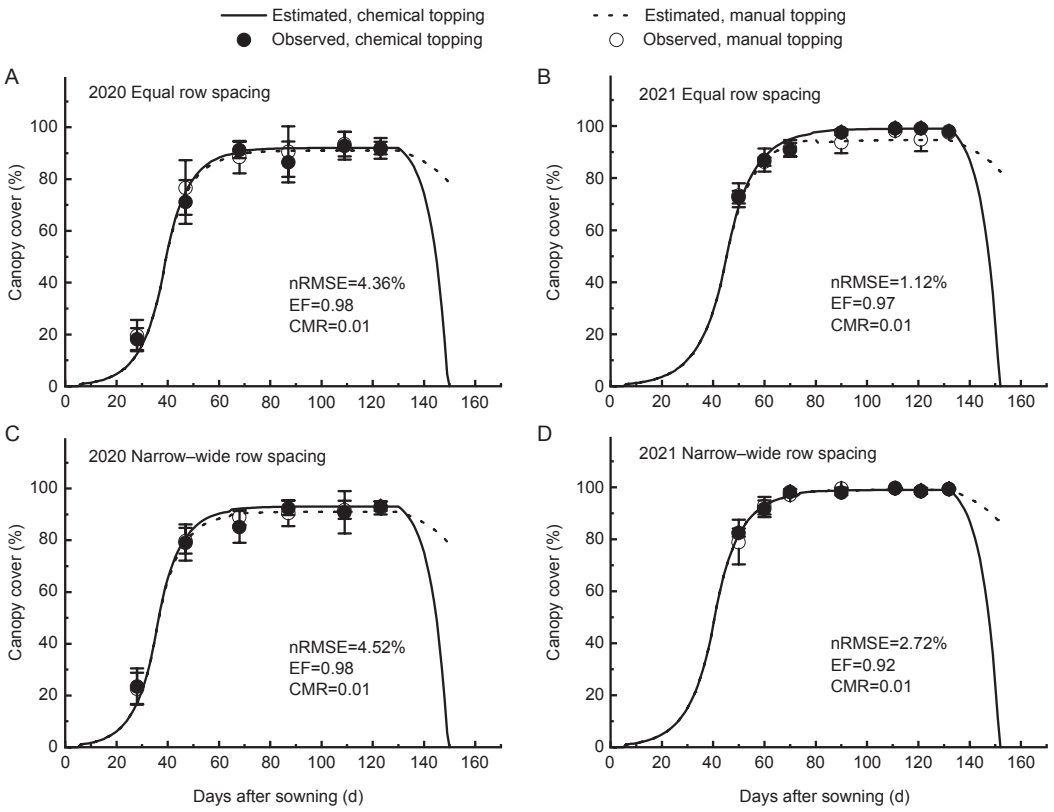


Fig. 2 Comparison of model-simulated canopy cover and the observations in 2020–2021. The values of normalized root mean square error (nRMSE), model efficiency (EF), and coefficient of residual mass (CMR) in the graphs represent the averages of the data from chemical and manual topping treatments. Bars mean SD (n=3).

Table 2 Statistical results of model-estimated canopy cover and transpiration compared with field-observed data in 2020–2021[1)]

Year	Parameter	Row spacing	Topping	nRMSE (%)	EF	CMR
2020	Canopy cover	Equal row spacing	Chemical	4.72	0.98	–0.01
			Manual	4.31	0.98	0.03
		Narrow–wide row spacing	Chemical	2.37	0.94	–0.01
			Manual	3.04	0.91	0.02
	Transpiration	Equal row spacing	Chemical	17.23	–0.95	–0.10
			Manual	24.11	–4.76	–0.12
		Narrow–wide row spacing	Chemical	23.96	–2.28	–0.14
			Manual	29.16	–3.81	–0.21
2021	Canopy cover	Equal row spacing	Chemical	5.24	0.97	–0.01
			Manual	3.25	0.99	0.02
		Narrow–wide row spacing	Chemical	1.05	0.97	0.01
			Manual	1.19	0.97	–0.01
	Transpiration	Equal row spacing	Chemical	15.69	–0.30	0.08
			Manual	17.80	–0.35	–0.02
		Narrow–wide row spacing	Chemical	20.05	–0.33	–0.17
			Manual	29.32	–2.26	–0.26

[1)] nRMSE, normalized root mean square error; EF, model efficiency; CMR, coefficient of residual mass.

in chemical topping than in manual topping in the field measurements. However, it showed negligible differences in the model simulations.

4. Discussion

The AquaCrop Model simulated CC in cotton growing under different topping and row spacing conditions showed good agreement (nRMSE=3.15%) with field measurements. The simulated transpiration exhibited a favorable correlation with observed values (nRMSE=22.4%). The overestimation of daily transpiration and underestimation of WUE may be attributed to the high weighting of CC in the model and simplistic calculation of Kc_{Tr}. Consequently, these factors also led to less pronounced variations in transpiration among

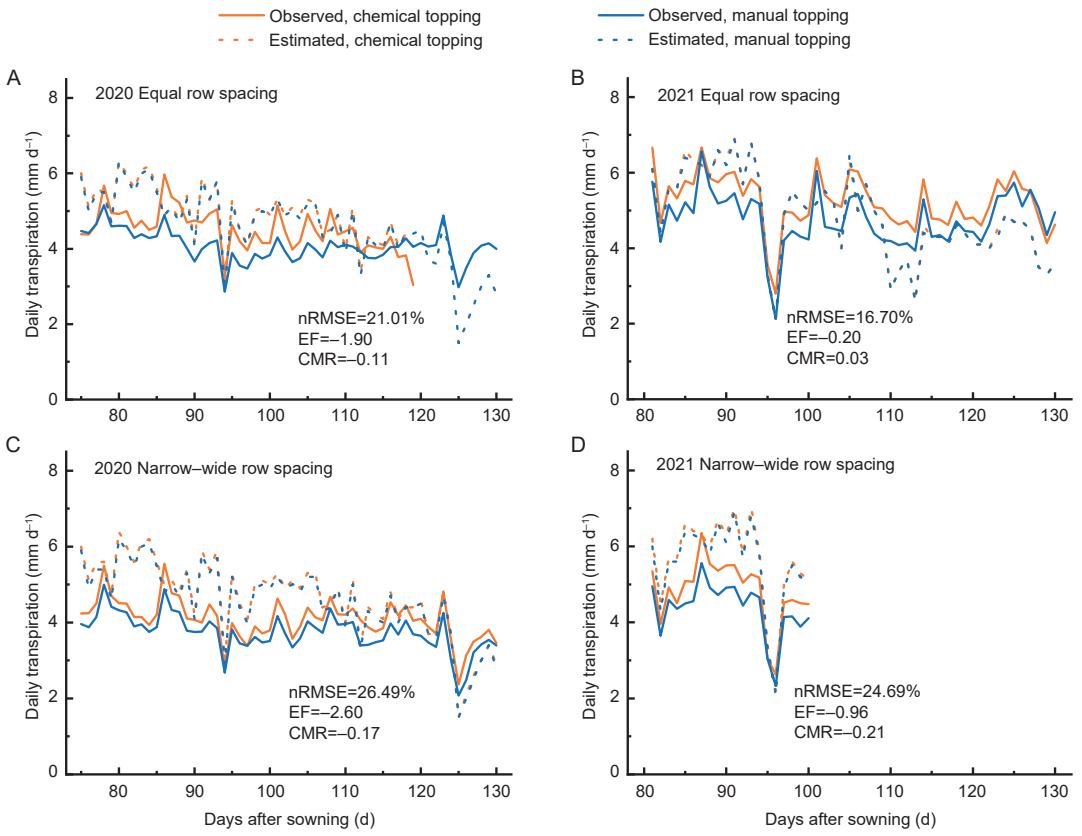


Fig. 3 Comparison of model-estimated and field-measured daily transpiration of cotton in 2020–2021. The values of normalized root mean square error (nRMSE), model efficiency (EF), and coefficient of residual mass (CMR) in the graphs represent the averages of the data from chemical and manual topping treatments.

Table 3 Statistical results of model-estimated total transpiration and water use efficiency compared with field-observed data in 2020–2021

Year	Row spacing	Topping	Biomass (g m^{-2})	Total transpiration (mm)[1)]		Water use efficiency (g m^{-2} mm^{-1})	
				Measured	Simulated	Measured	Simulated
2020	Equal row spacing	Chemical	1,432 a	243	259	5.20	4.83
		Manual	1,276 b	228	256	4.88	4.22
	Narrow–wide row spacing	Chemical	1,216 ab	229	260	5.01	4.38
		Manual	1,115 ab	210	255	4.62	3.77
2021	Equal row spacing	Chemical	1,743 a	270	249	4.60	5.17
		Manual	1,569 b	247	249	4.44	4.40
	Narrow–wide row spacing	Chemical	1,459 a	–	254	–	4.28
		Manual	1,430 ab	–	250	–	4.33

[1)] Total transpiration refers to the cumulative transpiration from cotton topping (days after sowning (DAS)=75) to harvest (DAS=130).
Same letters indicate no significant differences between the row spacing and topping treatments within the same year at the 0.05 level. –, no observed data were available.

the treatments. Moreover, the model accentuated the impact of meteorological factors on transpiration, resulting in a tendency toward overestimation during periods characterized by elevated temperatures and radiation. Therefore, the model might need further refinement to improve its accuracy by considering more crop growth parameters related to agronomic practices.

4.1. Overestimation of transpiration in the peak growing season

The AquaCrop Model overestimation of transpiration was mainly concentrated in July and August when the cotton CC reaches its maximum (91–99%). One reason is the model's overemphasis on CC in its evapotranspiration calculations, which results in almost all of the soil water being allocated to crop transpiration, while soil evaporation is almost nonexistent. While this approach establishes a more direct relationship between transpiration and crop growth, it inadequately simulates soil evaporation. He *et al.* (2021) noted that the AquaCrop Model accurately reflects actual evapotranspiration during the early stages of crop growth. However, as the canopy expands, the model tends to underestimate evaporation losses, leading

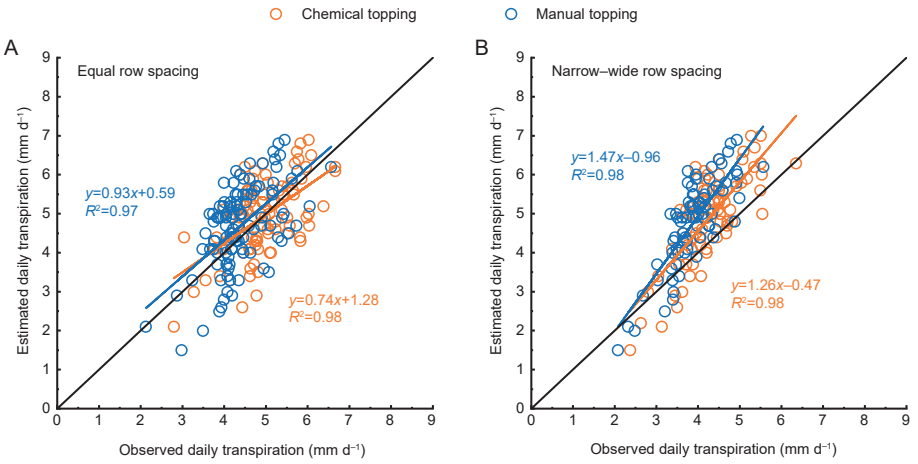


Fig. 4 Relationship between model-estimated and measured daily transpiration values in 2020–2021.

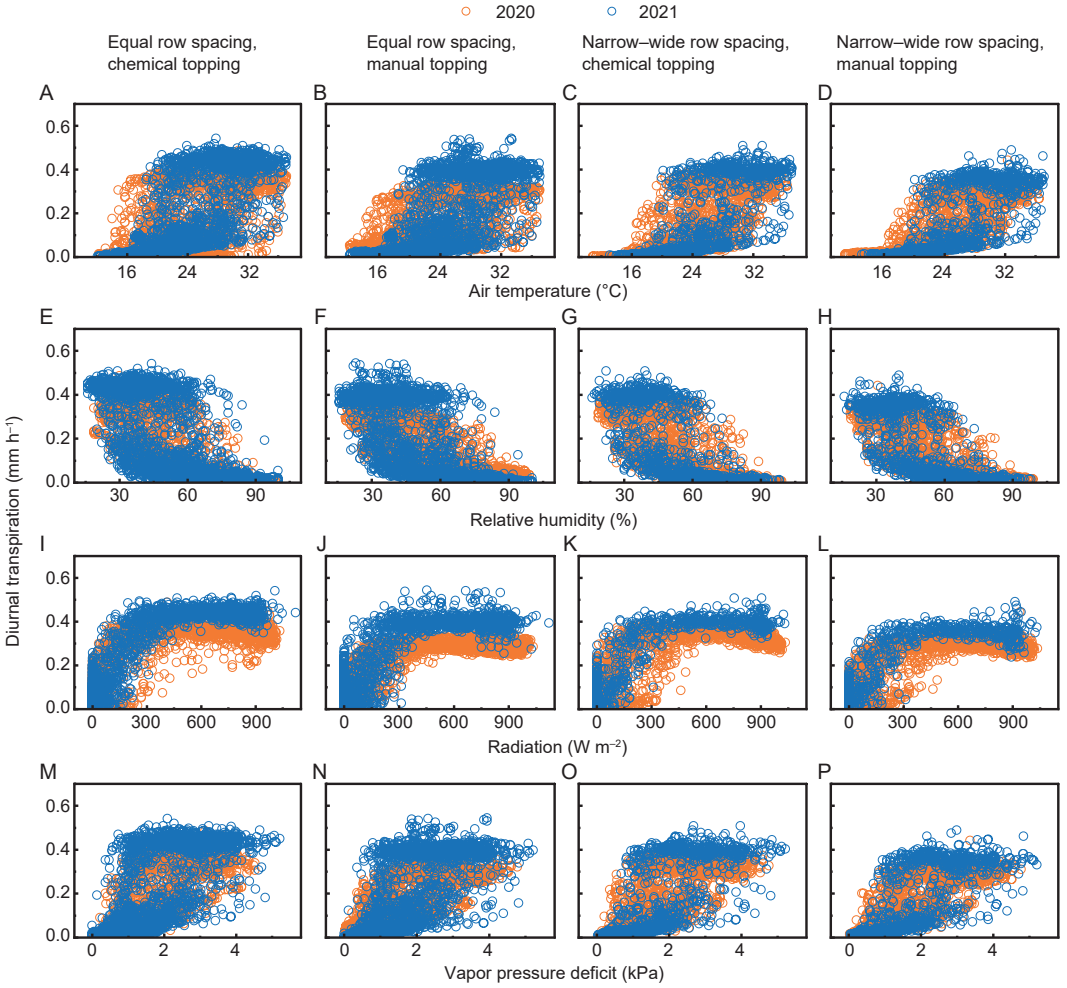


Fig. 5 Relationships between diurnal transpiration and climatic factors for different treatments of cotton from topping to defoliation in 2020–2021.

to higher transpiration estimations, which is consistent with our results. In addition, the heavy dependence of the model on the CC curve reduces the sensitivity of results to water stress, leading to increased transpiration even under drought conditions (Ran *et al.* 2017). Another reason is the potential limitation in the calculation of Kc_{Tr} by the model, which leads to an overestimation of transpiration and poor segment fitting (Chibarabada *et al.* 2020). The Kc_{Tr} parameter plays a crucial role in the estimation of crop transpiration as a linkage to crop canopy development, and it usually uses an empirical value

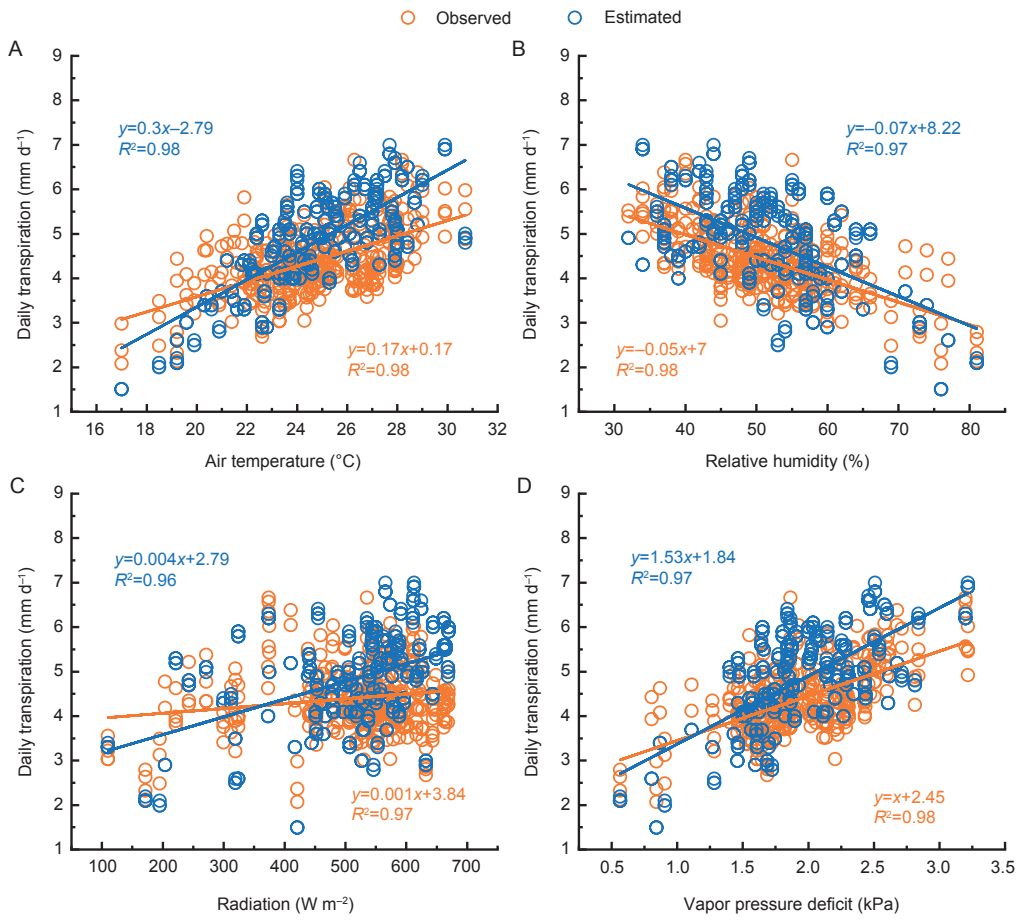


Fig. 6 Relationships between meteorological factors and daily transpiration from both model estimation and the measurements in 2020–2021.

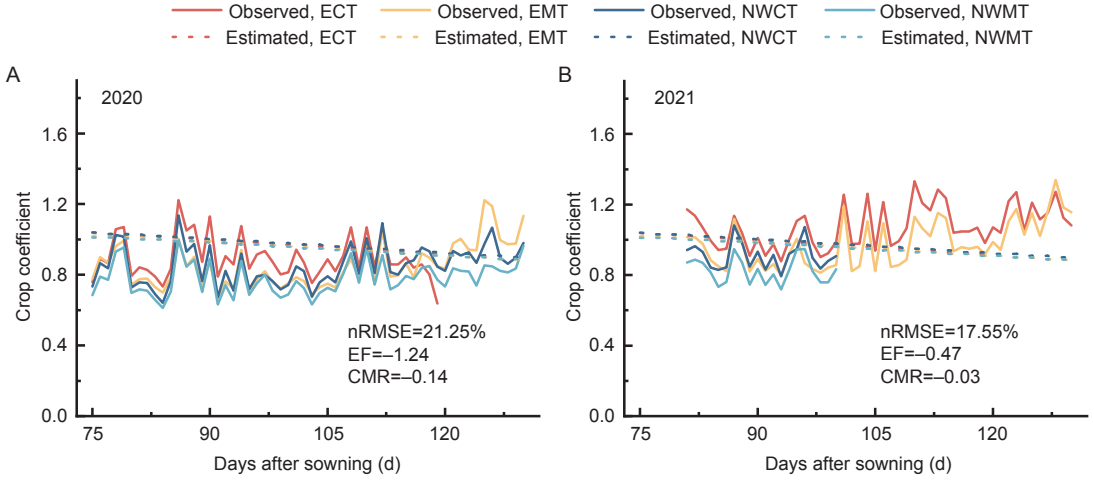


Fig. 7 Comparison of model-estimated and field-observed crop coefficients in cotton under different treatments in 2020 and 2021. ECT, equal row spacing, chemical topping; EMT, equal row spacing, manual topping; NWCT, narrow–wide row spacing, chemical topping; NWMT, narrow–wide row spacing, manual topping. The values of normalized root mean square error (nRMSE), model efficiency (EF), and coefficient of residual mass (CMR) in the graphs represent the averages of the data from all topping and row spacing treatments.

(or equation) in the model (Ahmadi *et al.* 2022). AquaCrop incorporates an aging factor, causing the Kc_{Tr} value to decrease at a fixed rate after reaching its maximum value (Steduto *et al.* 2009). However, according to our observations, that decline was relatively small. Our results suggested a maximal Kc_{Tr} value of 1.2 for plastic film mulching and drip-irrigated cotton in Xinjiang while a previous study suggested around 1.1 for similar situations (Han *et al.* 2019).

4.2. Limitations in model sensitivity to agronomic factors

All the major output components of AquaCrop, such as crop transpiration, soil evaporation, and biomass, are directly linked to the CC curve, potentially leading to misleading outcomes in certain scenarios (Sandhu and Irmak 2019). Chemical topping can achieve a more compact plant architecture (Dai *et al.* 2022), allowing more light penetration to the lower canopy layer, thereby increasing the crop photosynthetic area and transpiration. Row spacing alters canopy light distribution and interception, likely affecting plant transpiration (Gao *et al.* 2024). However, the model is unable to incorporate these processes. Cotton in Xinjiang is often densely planted, resulting in greater CC (Wu *et al.* 2023). However, the CC_X is similar across different treatments, resulting in insignificant differences in crop transpiration simulated by the model. In addition to canopy growth parameters, root development-related factors might also play a significant role in crop transpiration in the AquaCrop Model (Lu *et al.* 2021). We used same root-related parameters, e.g., maximum effective rooting depth (Zx), in the model, which might introduce some estimation errors.

4.3. Inadequate representation of climatic factors and their impact

Climatic factors such as air temperature, relative humidity, and solar radiation play critical roles in crop transpiration. We found that the AquaCrop Model amplified the effect of air temperature on crop transpiration. While the model incorporates a stress coefficient to adjust for the impact of low-temperature stress on crop transpiration, it does not consider limitations under high temperature and radiation conditions (Vanuytrecht *et al.* 2014). VPD plays a critical role in driving crop transpiration, as high VPD typically reduces stomatal conductance, leading to greater transpiration in many plant species (Grossiord *et al.* 2020). The model simplifies this relationship using a basic threshold, but it may fail to capture the full range of VPD effects on transpiration. Genotype can also affect crop responses to high temperature and vapor pressure deficit (Broughton and Conaty 2022), but the model does not take this into account. Furthermore, elevated wind speeds can affect crop transpiration by promoting water loss through increased evaporation and altering stomatal conductance (Shapira *et al.* 2024). The sap flow measurements showed a transient reduction in cotton transpiration at noon time, which is probably linked to stomatal closure resulting from the lowest leaf water potential under high temperature and strong radiation conditions (Yang *et al.* 2023).

4.4. Improving model reliability: Calibration and future optimization strategies

Most models require complex parameter calibration and validation processes to achieve relatively accurate results (Pasley *et al.* 2023). In this study, the transpiration data used for model calibration were obtained from the heat ratio method-based measurement of cotton sap flow. As a direct indicator of crop water use, sap flow data provides a precise representation of the transpiration process (Poyatos *et al.* 2020), thereby ensuring robust and reliable validation of the model. Plant variability was analyzed prior to installing the sap flow meter, and relatively average samples were selected. A wound correction factor was used to reduce data drift caused by mechanical damage during drilling (Steppe *et al.* 2010), thereby minimizing bias and uncertainty in the data. The validation results demonstrated that the model successfully captured the dynamics of transpiration over the crop growth period, although it slightly overestimated the values. To improve the accuracy of the model, future efforts should prioritize optimizing the evapotranspiration calculation module, dynamically adjusting the Kc_{Tr}, improving the canopy radiation interception calculations (Gu *et al.* 2024), and enhancing its sensitivity to meteorological factors. Furthermore, integrating multi-scale data — including remote sensing data (e.g., normalized difference vegetation index (NDVI), soil moisture), field-measured data (e.g., sap flow, soil respiration), and high-resolution meteorological data — could significantly enhance the generalizability of this model across different spatial and temporal scales (Huang *et al.* 2015; Battude *et al.* 2016). These advancements would allow the AquaCrop model to simulate crop water use more effectively under diverse growth stages and climatic conditions, thereby expanding its applicability and predictive reliability.

5. Conclusion

Overall, the AquaCrop Model accurately predicted water use in cotton with plastic film mulching and drip irrigation. However, it tended to overestimate transpiration during the growing season and showed insufficient sensitivity to both climatic and agronomic factors. Model accuracy could be enhanced by revising the evaporation and Kc_{Tr} calculation modules, incorporating more dynamic climatic data, and including detailed agronomic practices. These modifications would allow the model to better capture transpiration and water use efficiency, and improve its adaptability to complex climatic conditions and diverse agronomic environments. Our results provide valuable insights into the application of the AquaCrop Model in machine-harvested cotton farming, while also offering key directions for future improvements in crop simulation models.

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Declaration of competing interest

The authors declare that they have no conflict of interest.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used ChatGPT 4.0 to assist in improving the clarity and readability

of the language. All content generated was carefully reviewed and revised by the authors as necessary, and the authors take full responsibility for the final content of the article.

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