Postprint: Jujube Growth Simulation and Water Use Evaluation Based on a Calibrated WOFOST Model

Authors: Bai Tiecheng, Wang Tao, Zhang Nannan

Date: 2023-02-17T00:00:00+00:00

Abstract

To quantitatively analyze the effects of temperature, light, and water resources on fruit tree growth, this study proposes a simulation method for jujube tree growth and water transport based on a calibrated WOFOST model, using mature Jun jujube trees as the research object. Using field experimental observation data from 2016 and 2017, the phenological development, initialization, green leaf, CO2 assimilation, dry matter partitioning, respiration, and water use parameters of the WOFOST model were calibrated. At the field scale, dynamic simulation and accuracy validation were completed for total aboveground biomass (TAGP), leaf area index (LAI), and soil moisture content; at the county scale, data from 55 orchards including maximum LAI, yield, actual evapotranspiration (ETa), and water use efficiency (WUE) were used to evaluate the model' s simulation performance at the regional scale. The results showed that at the field scale, the coefficient of determination (R^2) for simulated TAGP under different irrigation gradients by the calibrated model ranged from 0.92 to 0.98, with normalized root mean square error (NRMSE) of 8.7% to 20.5%; R^2 for simulated LAI ranged from 0.79 to 0.97, with NRMSE of 8.3% to 21.1%; R^2 for simulated soil moisture content ranged from 0.29 to 0.75, with NRMSE of 4.1% to 6.1%. At the county scale, R^2 values between simulated and measured maximum LAI for the two years were 0.64 and 0.78, respectively, with NRMSE of 13.3% and 10.7%; R^2 for simulated yield were 0.48 and 0.60, respectively, with NRMSE of 12.1% and 11.9%; root mean square error for simulated ETa was 36.1 mm (7.9%) and 30.8 mm (7.4%), respectively; the model also demonstrated high simulation accuracy for WUE (10%

Full Text

Dynamic Simulation of Jujube Tree Growth and Water Use Evaluation Based on the Calibrated WOFOST Model

BAI Tiecheng[1]*, WANG Tao[1], ZHANG Nannan[1,2]

[1]College of Information Engineering/Southern Xinjiang Research Center for Information Technology in Agriculture, Tarim University, Alaer 843300, China
[2]College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China

Abstract

Irrigation schemes determined through statistical analysis of field trials are typically only applicable to specific soil and meteorological conditions, making it difficult to quantitatively analyze the impacts of irrigation strategies on jujube tree growth. To realize quantitative analysis of temperature, light, and water resource effects on fruit tree development, this study employed the WOrld FOod Studies (WOFOST) model to simulate jujube tree growth and water migration processes. Using observed data from field trials conducted in 2016 and 2017, we calibrated the phenological development, initialization, green leaf, CO_2 assimilation, dry matter partitioning, respiration, and water use parameters of the WOFOST model for mature *Ziziphus jujuba* cv. Jun trees. At the field scale, we performed dynamic simulation and accuracy verification of total above-ground biomass (TAGP), leaf area index (LAI), and soil moisture content. At the county scale, we evaluated model performance using maximum LAI, yield, actual evapotranspiration (ETa), and water use efficiency (WUE) data from 55 orchards.

Results demonstrated strong model performance at the field scale: TAGP simulations achieved coefficients of determination (R^2) between 0.92 and 0.98 with normalized root mean square errors (NRMSE) of 8.7%-20.5%; LAI simulations yielded R^2 values of 0.79–0.97 and NRMSE of 8.3%-21.1%; soil moisture content simulations showed R^2 of 0.29–0.75 and NRMSE of 4.1%-6.1%. The model effectively captured temporal dynamics of jujube growth and soil moisture changes. At the county scale, simulated versus measured maximum LAI produced R^2 of 0.64 and 0.78, with NRMSE of 13.3% and 10.7% for 2016 and 2017, respectively. Yield simulations achieved R^2 of 0.48 and 0.60, with NRMSE of 12.1% and 11.9%. ETa simulations exhibited RMSE of 36.1 mm (7.9%) and 30.8 mm (7.4%), demonstrating exceptional accuracy (NRMSE $<$ 10%). WUE simulations also showed high accuracy (10% $<$ NRMSE $<$ 20%) with RMSE values of 0.23 and 0.28 kg/m^3. In summary, the calibrated WOFOST model achieved accurate simulation of jujube tree growth and water transport at both field and county scales, providing a new approach for quantitative and mechanistic analysis of coupled soil, meteorological, irrigation management, and tree growth effects.

Keywords: crop growth model; parameter calibration; WOFOST; jujube tree; water use efficiency

1. Introduction

Jujube fruit is rich in proteins, carbohydrates, vitamins, and minerals, holding significant nutritional and medicinal value. China is the world' s largest jujube producer, with Xinjiang alone accounting for 3.728 million tons annually—approximately 50% of national production—making it a crucial pillar industry for farmer income and population concentration in southern Xinjiang. However, the region faces extreme continental arid desert climate conditions with high summer temperatures, intense evapotranspiration, and scarce rainfall. Water resource scarcity presents a critical challenge, and quantitative evaluation of evapotranspiration and water use efficiency represents a key technical issue for water-saving agriculture in arid regions.

Existing research on jujube water effects and irrigation management has primarily focused on irrigation impacts on yield and quality, soil moisture responses to management practices, optimization of water-fertilizer management, and coupled irrigation-fertilization effects on yield. However, these studies predominantly rely on field trial data, with irrigation schemes applicable only to specific soil and climate conditions, preventing quantitative analysis of irrigation strategy impacts on jujube yield and quality.

Crop growth models based on physiological and ecological principles use mathematical formulations to quantify crop development under climate, soil, and management influences. Several mature models have been developed over recent decades, including WOFOST (WOrld FOod Studies), DSSAT (Decision Support System for Agrotechnology Transfer), and EPIC (Environmental Policy Integrated Climate). These models typically incorporate phenology, CO_2 assimilation, respiration, assimilate partitioning, and soil water cycling modules, finding widespread application in agricultural management, climate change response, yield prediction, and coupled environment-water-crop growth analysis.

Most crop growth models focus on annual field crops. In fruit tree modeling, Fishman and Génard developed a peach fruit growth model based on water and dry matter transport mechanisms to analyze seasonal and diurnal fruit growth under water stress conditions. López et al. created a three-dimensional peach growth simulation model for pruning management. Lescourret et al. integrated orchard management inputs into a global model explaining flowering, pollination, and fruit growth relationships in kiwifruit, demonstrating sensitivity to climate and technical operations. Green et al. developed a canopy transpiration and light interception model showing that light interception is most sensitive to leaf area and optical properties, while transpiration responds primarily to leaf area and conductance. Costes et al. simulated apple tree development using mixed stochastic and biomechanical models.

However, reported fruit tree growth models lack mechanistic descriptions of physiological and biochemical processes. WOFOST is a mechanistic model that explains crop growth through phenology, CO_2 assimilation, transpiration, respiration, and environmental responses. Its generic process descriptions enable parameter calibration for different crops, water-limited yield assessment, and have demonstrated potential for jujube growth simulation and yield evaluation. Implementing perennial fruit tree water-limited growth simulation in WOFOST could enable quantitative analysis of coupled soil-meteorology-irrigation-management effects, advancing fruit tree irrigation management from statistical analysis to quantitative mechanistic description.

Therefore, this study calibrated WOFOST model parameters using field-measured jujube physiological and biochemical indicators and soil physico-chemical data to simulate jujube growth and water migration processes. We validated simulation accuracy at the field scale using measured TAGP, LAI, and soil moisture content, and evaluated county-scale performance using maximum LAI, yield, ETa, and WUE from 55 orchards.

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2. Materials and Methods

2.1 Study Area Overview

The study area is located in Alaer City, Xinjiang Uygur Autonomous Region (80°30 E–81°58 E, 40°22 N–40°57 N), with approximately 45,000 hectares of jujube cultivation—about one-eighth of national production. The region experiences a warm temperate extreme continental arid desert climate. Annual rainfall was 106 mm in 2016 and 98 mm in 2017, primarily distributed in summer. Annual solar radiation ranges from 133.7–146.3 kcal/cm^2, with 2,556.3–2,991.8 sunshine hours annually. Mean annual temperature is 10.8–12.5 °C, with maximum daily temperature differences reaching 20 °C. Abundant light and heat resources provide favorable natural conditions for high-quality jujube cultivation.

2.2 Experimental Design

Field trials were conducted in 2016 and 2017 in a mature jujube orchard (blue square area in [Figure 1: see original paper]) using five irrigation gradients during the growing season (excluding winter and spring irrigation): CK (375 mm, D1), 90% CK (338 mm, D2), 80% CK (300 mm, D3), 70% CK (263 mm, D4), and 60% CK (225 mm, D5). Irrigation quotas referenced local empirical values, with 10 applications per season. Fertilizer rates and other agronomic practices were identical across plots.

At the county scale, 55 jujube orchards were monitored (red dot coordinates in [Figure 1: see original paper]) for initial trunk dry weight, maximum development stage LAI, final yield, and actual evapotranspiration. LAI observations were conducted on July 24, 2016 and July 27, 2017, with yield measured in November. Actual evapotranspiration (ETa) was calculated using Equation (1):

$$ET_a = P_r + I - D - \Delta SM$$

where P_r, I, D, and ΔSM represent effective rainfall, irrigation amount, deep soil percolation, and soil moisture content difference between growing season start and end, respectively. Jujube root systems in Xinjiang are primarily distributed in 0-100 cm soil depth (mainly within 60 cm vertical depth). Deep percolation was measured at 100 cm depth. Groundwater is deep and surface runoff is minimal, so these factors were not considered.

Water use efficiency (WUE), a critical indicator for water-saving agriculture in arid regions, was calculated as the ratio of measured yield to ETa for further validation.

2.3 Test Items and Methods

Phenological Development Timing: Budbreak, flowering (fruit set), and maturity dates were recorded.

Dry Weight Measurement: Samples were collected every 10 days (10 times per season). Three uniform trees were selected each time, with all leaves, new shoots, and fruits harvested, oven-dried at 80 °C to constant weight, and organ dry weights measured.

Photosynthetically Active Radiation and LAI: Effective LAI at different canopy positions was measured every 10 days using a SunScan canopy analyzer (Delta-T Devices, UK).

Photosynthesis: Net photosynthetic rate, stomatal conductance, intercellular CO_2 concentration, and transpiration rate were measured every 10 days using a LI-6400XT portable photosynthesis system.

Soil Moisture: Soil volumetric water content was measured at 0-100 cm depth in 20 cm increments before and after irrigation using an auger (14 measurements annually).

Other Soil Parameters: Field capacity, bulk density, saturated water content, soil water response curves, and hydraulic conductivity were measured in the laboratory. Irrigation dates and amounts were recorded.

Meteorological Data: Provided by a micrometeorological station at Tarim University' s Jujube Research Base, including 15-minute interval temperature, humidity, radiation, wind speed, rainfall, and atmospheric pressure.

2.4 WOFOST Model Parameter Calibration

WOFOST parameters include meteorological, soil, and crop parameters. Meteorological data from the station were used directly due to minimal spatial variability at county scale. Soil property parameters used measured values. This study focused on crop parameter calibration.

Calibration Procedure:

1. **Phenological Parameters:** Calibrated using effective accumulated temperature method. The lower threshold temperature for emergence (TBASEM) was set to 10 °C based on literature. The maximum effective temperature for emergence (TEFFMX) was set to 30 °C, as temperatures during budbreak in 2016–2017 remained below 30 °C without heat stress. Temperature sums from sowing to emergence (TSUMEM), emergence to anthesis (TSUM1), and anthesis to maturity (TSUM2) were calibrated using daily mean temperatures and observed phenological dates. Daily temperature sum increase (DTSMTB) was calculated using optimal upper temperature (35.5 °C) and lower development temperature (10 °C).

2. **Initial Dry Weight:** Unlike annual crops, jujube initial dry weight was defined as new organ weight (buds and roots) to avoid overestimation from previous year' s stems. Initial dry weight (TDWI) was calibrated using simulated and measured TAGP and LAI from 2016 D1 treatment. County-scale initial trunk dry weights for 55 orchards were calculated from measured bud weight and allocation coefficients derived from field trials.

3. **Green Leaf Parameters:** Measured LAI at emergence (LAIEM) was <0.004 across all plots. Simulations showed minimal differences in TAGP, leaf dry weight, stem dry weight, fruit dry weight, and LAI when LAIEM varied from 0.0007 (WOFOST minimum) to 0.01, so LAIEM was set within this range. Maximum relative LAI increase (RGRLAI) was <0.05; increasing RGRLAI to the default maximum of 0.5 produced negligible changes in TAGP and LAI, so RGRLAI was set to the minimum value of 0.05. Specific leaf area (SLATB) was calibrated using measured TAGP and LAI. Leaf lifespan parameter (SPAN) was calibrated using late-season LAI measurements.

4. **CO_2 Assimilation Parameters:** Light response curves were fitted at optimal development temperatures (19.5 °C lower, 35.5 °C upper) to obtain initial values for maximum leaf CO_2 assimilation rate (AMAXTB) and light-use efficiency (EFFTB). Extinction coefficient for diffuse visible light (KDIFTB), AMAXTB, and EFFTB were then calibrated using measured TAGP and LAI.

5. **Dry Matter Partitioning:** Partitioning coefficients to stems (FSTB), fruits (FOTB), and leaves (FLTB) as functions of development stage were calibrated using measured and simulated above-ground organ dry weights.

6. **Water Use Parameters:** Measured soil moisture content was used to calibrate transpiration rate correction factor (CFET), crop water stress sensitivity correction factor (DEPNR), initial rooting depth (RDI), maximum daily root depth increase (RRI), and maximum rooting depth (RDMCR).

2.5 Model Validation

Model validation comprised two components. At the field trial site, 2017 D1-D5 treatment measurements of time-series TAGP, LAI, and soil moisture content validated growth and water transport simulation accuracy. County-scale measurements from 55 orchards (maximum LAI, yield, ETa, and WUE) evaluated regional simulation performance.

Statistical metrics included coefficient of determination (R^2), root mean square error (RMSE), normalized root mean square error (NRMSE), relative bias error (RBE) frequency distribution, and coefficient of variation (CV). R^2 indicates consistency between measured and simulated values; RMSE and NRMSE represent relative and absolute errors. NRMSE <10% indicates extremely high accuracy, 10–20% high accuracy, 20–30% moderate accuracy, and >30% low accuracy. CV reflects spatial variability: CV <10% weak, 10–100% moderate, >100% strong. RBE frequency distribution indicates over- and under-estimation proportions.

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3. Results

3.1 Model Parameter Calibration

Calibrated jujube crop parameters are presented in , with values derived from measurements (m), calibrated measurements (m-c), estimates (e), calibrations (c), and literature references.

3.2 Field Validation

The 2016 D1 treatment data calibrated model parameters, while 2017 D1-D5 treatment time-series data validated simulation accuracy.

3.2.1 TAGP and LAI Validation TAGP and LAI simulation accuracy are critical indicators of jujube growth simulation performance. shows validation results across treatments. D1-D3 TAGP simulations showed strong agreement with measurements ($R^2 > 0.94$) and high accuracy ($8.7\% \leq$ NRMSE $\leq 16.9\%$). D4 and D5 TAGP simulations performed slightly lower ($R^2 = 0.92$, NRMSE 20%). D1-D4 LAI simulations demonstrated high consistency and accuracy ($R^2 > 0.9$, NRMSE $< 15\%$), while D5 showed reduced performance ($R^2 = 0.79$, NRMSE $> 20\%$). This suggests that as irrigation decreased and water stress intensified, the calibrated model' s ability to simulate stress responses may decline. Overall, the model exhibited satisfactory TAGP and LAI simulation performance at 70-100% of the reference irrigation amount.

3.2.2 Soil Moisture Content Validation Simulated versus measured soil moisture content for D1-D5 treatments is shown in [Figure 2: see original paper]. Measured and simulated values showed consistent overall trends, with R^2 ranging from 0.29 to 0.75, RMSE from 0.010 to 0.013, and NRMSE from 4.1% to 6.1%. D4 and D5 treatments showed slightly lower consistency ($R^2 < 0.5$) compared to D1-D3. All treatments achieved extremely high soil moisture simulation accuracy (NRMSE < 6.1%) with small absolute errors.

Comprehensive evaluation of TAGP, LAI, and soil moisture metrics indicated high consistency and simulation accuracy when irrigation amounts were $ $80% of the empirical rate. Although D4 and D5 treatments showed slightly reduced performance for TAGP and LAI, maximum absolute errors remained acceptable. The model demonstrated extremely high soil moisture simulation accuracy (NRMSE < 10%) across all irrigation treatments.

3.3 County-Scale Validation

3.3.1 Maximum LAI Validation The model was run using measured initial trunk dry weight parameters from 55 orchards. Scatter plots of simulated versus measured maximum LAI are shown in [Figure 3: see original paper]. In 2016 and 2017, simulated maximum LAI achieved R^2 of 0.64 and 0.78, respectively, with NRMSE of 13.3% and 10.7%, indicating good consistency and high accuracy. Simulated LAI coefficient of variation (CV) values were 21.6% and 21.2%, expressing significant spatial variability that reflects the spatial heterogeneity of initial trunk dry weight distribution.

3.3.2 Yield Validation Simulated versus measured yield showed R^2 of 0.48 and 0.60 in 2016 and 2017, respectively ([Figure 4: see original paper]), with RMSE of 0.83 and 0.94 kg/ha, and NRMSE of 12.1% and 11.9%, demonstrating high yield prediction accuracy (NRMSE < 20%). High-yield regions were notably underestimated, likely due to factors including CO_2 assimilation parameters, dry matter partitioning, leaf area-to-weight ratio, and leaf senescence rate. The fixed leaf senescence rate parameter (50) may be lower than actual values (40-60) in some county-scale orchards, leading to underestimation of high-yield areas.

Relative error frequency distributions for yield simulation ([Figure 5: see original paper]) showed most samples clustered near y=0, with mean relative errors of 3.23% and 2.94%, and mean absolute relative errors of 9.72% and 9.68%, indicating high accuracy. In 2016 and 2017, 61.8% and 63.6% of samples were underestimated, respectively, suggesting spatial variability in leaf senescence rates may reduce simulation accuracy. CV values of 12.5% and 11.9% indicated moderate yield spatial variability, likely caused by differences in tree age and planting density affecting initial trunk dry weight heterogeneity.

3.3.3 Actual Evapotranspiration and WUE Validation Relative error frequency distributions for simulated ETa and WUE across 55 orchards are shown in [Figure 6: see original paper]. All orchards showed ETa simulation errors <20%, with 49 orchards <10%. RMSE values were 36.1 mm (7.9%) and 30.8 mm (7.4%) for 2016 and 2017, respectively, demonstrating exceptional accuracy (NRMSE < 10%). Mean relative errors were slightly positive in 2016 and negative in 2017, with mean absolute values of 6.44% and 5.98%.

WUE relative errors were slightly higher than ETa. In both growing seasons, 50.9% (2016) and 47.3% (2017) of samples showed <10% error, while 85.5% and 80% showed <20% error, with maximum errors of 37.4% and 38.3%. The calibrated model demonstrated high WUE simulation accuracy (10% < NRMSE < 20%), with RMSE values of 0.23 and 0.28 kg/m^3.

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4. Discussion

4.1 Field-Scale Simulation Accuracy Analysis

Field-scale validation showed that time-series TAGP and LAI simulations achieved moderate to high accuracy, while soil moisture content achieved extremely high accuracy (4.1% $\leq$ NRMSE $\leq$ 6.1%). The D1 treatment in 2016 approached potential water supply conditions. In 2017, D1–D3 treatments received >80% of the control irrigation amount, creating minimal water stress and yield impacts similar to 2016 D1. D4 and D5 treatments likely caused more severe drought stress, with actual production impacts potentially exceeding simulated drought stress corrections, leading to TAGP and LAI simulation errors. LAI simulation biases would subsequently affect transpiration and soil evaporation calculations, reducing soil moisture simulation accuracy compared to D1–D3.

Additionally, jujube growth in field conditions is affected by fertilization, pests, diseases, wind, and heat stress—factors the model cannot currently respond to. Integrating classical nitrogen transport modules or pest/disease response models into the calibrated jujube growth model could further improve simulation accuracy and mechanistic representation.

4.2 Uncertainty in Regional-Scale Model Application

When running WOFOST for growth simulation and yield assessment, uncertainties in input parameters, meteorological driving data, and model simplifications affect yield estimation accuracy. Primary expected error sources include input parameter uncertainty, particularly initial trunk dry weight, which strongly influences initial growth rates and shows high uncertainty, potentially affecting initial and maximum LAI development rates and consequently growth simulation and yield assessment accuracy.

Using measured initial trunk dry weight from 55 orchards to drive county-scale simulations achieved high accuracy for maximum LAI and yield (NRMSE < 20%), confirming substantial spatial heterogeneity in initial trunk dry weight across county-scale orchards. Previous studies using average initial trunk dry weight from same-age orchards reported yield validation NRMSE of 16.3% (2016) and 17.2% (2017) across 181 regional orchards—significantly higher than this study' s 12.1% and 11.9% errors—demonstrating that initial trunk dry weight is a highly sensitive parameter.

Although leaf senescence rate depends primarily on crop genetics, it is also affected by drought, nutrient stress, pests, diseases, and management practices. WOFOST cannot simulate these effects on leaf senescence rate. The fixed value of 50 used in this study cannot represent actual conditions across all 55 samples, and errors in simulated maximum LAI most likely stem from spatial variability in leaf senescence rates. Previous studies assimilating remotely-sensed LAI into WOFOST using EnKF and SUBPLEX algorithms reduced uncertainties in initial trunk dry weight and leaf senescence rate, improving county-scale yield simulation accuracy to NRMSE of 9.2% and 8.3%. This indicates that initial trunk dry weight and leaf senescence rate are uncertainty parameters for regional-scale simulation, and remote sensing assimilation could reduce this uncertainty.

Furthermore, spatial heterogeneity in soil properties at regional scales affects maximum LAI and water transport simulation accuracy. Assimilating remotely-sensed LAI and ETa state variables could reduce soil moisture simulation uncertainty and improve yield assessment. Therefore, county-scale yield and evapotranspiration simulation errors may originate from uncertainties in initial trunk dry weight, leaf senescence rate, and soil properties caused by irrigation, fertilization, and pruning management. Future research should assimilate soil moisture, evapotranspiration, and LAI state variables to calibrate these parameters and improve regional-scale simulation accuracy, providing mechanistic models for analyzing water stress impacts on jujube growth and yield at regional scales.

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