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Optimizing Irrigation Strategies to Improve Water Use Efficiency of Cotton in Northwest China Using RZWQM2

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Abstract: Irrigated cotton (*Gossypium hirsutum* L.) is produced mainly in Northwest China, where groundwater is heavily used. To alleviate water scarcity and increase regional economic benefits, a four-year (2016–2019) field experiment was conducted in Qira Oasis, Xingjiang Province, to evaluate irrigation water use efficiency (IWUE) in cotton production using the Root Zone Water Quality Model (RZWQM2), that was calibrated and validated using volumetric soil water content (θ), soil temperature (T°_{soil}) and plant transpiration (T), along with cotton growth and yield data collected from full and deficit irrigation experimental plots managed with a newly developed Decision Support System for Irrigation Scheduling (DSSIS). In the validation phase, RZWQM2 adequately simulated (S) topsoil θ and T°_{soil}, as well as cotton growth (average index of agreement (IOA) > 0.76). Relative root mean squared error (RRMSE) and percent bias (PBIAS) of cotton seed yield were 8% and 2.5%, respectively, during calibration, and 20% and −10.3% during validation. The cotton crop's (M) T was well S (−18% < PBIAS < 14% and IOA > 0.95) for both full and deficit irrigation fields. The validated RZWQM2 model was subsequently run with seven irrigation scenarios with 850 to 350 mm water (Irr850, Irr750, Irr700, Irr650, Irr550, Irr450, and Irr350) and long-term (1990–2019) weather data to determine the best IWUE. Simulation results showed that the Irr650 treatment generated the greatest cotton seed yield (4.09 Mg ha^{-1}) and net income (US $3165 ha^{-1}), while the Irr550 treatment achieved the greatest IWUE (6.53 kg ha^{-1} mm^{-1}) and net water production (0.94 $ m^{-3}). These results provided farmers guidelines to adopt deficit irrigation strategies.

Keywords: RZWQM2; DSSIS; long-term irrigation; cotton seed yield; IWUE

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1. Introduction

Optimizing agricultural irrigation scheduling contributes to alleviating competition for water, especially in regions where groundwater resources are limited. Cotton (*Gossypium hirsutum* L.) is the most important natural fiber, food, and fuel crop in the world. China is the world's largest producer and consumer of cotton. Eighty percent (80%) of China's cotton-growing area is in the Xinjiang Uygur Autonomous Region (XUAR) with 25,000 km^2 and 5.16 Tg y^{-1} cotton production representing 87% of national production. Cotton irrigation in the XUAR consumes 12.4 billion m^3 y^{-1} of water, roughly a quarter of total agricultural water use in the region. Groundwater use in the XUAR reached 11.8 billion m^3 y^{-1}, exceeding recommended levels of use by 57%, and resulting in a significant decrease in groundwater table [1]. Despite the implementation of water-saving practices (e.g., drip irrigation) and policies (e.g., raising water prices), the water use efficiency (WUE) for cotton remains between 0.43 and 0.73 kg m^{-3} [2], which are low values compared to those for other regions. The irrigation water use efficiency (IWUE) of cotton varied between 1.0 to 1.2 kg m^{-3} in the Texas High Plains (THP) region, USA [3]. Therefore, maintaining a sustainable irrigation strategy is particularly important in arid northwest China.

Long-term field experiments are key to formulating irrigation schedules that can improve cotton crop WUE. Several studies have reported irrigation scheduling decision support systems (DSS) or deficit irrigation protocols (DI) to improve the WUE of cotton [4–7]. In recent years, the soil water content [8,9], plant crop temperature [10,11] and agriculture system models [12,13] have been widely applied in automated DSS to determine irrigation time and amount. Cotton being a drought–tolerant crop, through short–term field experiments, has shown better performance by implementing DI than other irrigation methods in terms of crop yields and WUE [14,15]. Compared with field control experiments, cropping system models have the advantages of low cost, high efficiency, and easy control of variables and have been widely used [16]. Cropping system models, once calibrated and validated, can serve as a surrogate in studying the effects of long-term irrigation scheduling and environmental parameters on crop yield under inter-annual climate variability [17,18]. Irrigation scheduling and its long-term impact on crop yield under limited irrigation is facilitated by using cropping systems models. Puntel et al. [19] reported that the Agricultural Production Systems sIMulator (APSIM) effectively simulated (S) the long-term effects of different nitrogen rates on corn yield and winter wheat–summer maize yields in central Iowa, USA. Examples of others are given by Zhao et al. [20], Li et al. [21], Lu et al. [22], Kothari et al. [23], Marek et al. [24], Masasi et al. [25], Mompremier et al. [26], Attia et al. [27] and Spivey et al. [28]. Long-term simulations of agricultural management strategies on crop yield are mainly concentrated in semi-arid and arid regions. Studies on the long-term effects of irrigation practices on crop WUE and economic profitability are rare in desert oasis regions.

We selected the Root Zone Water Quality Model (RZWQM2) to evaluate cotton seed yield and WUE. The RZWQM2, a hybrid model between RZWQM and DSSAT4.0, has been applied to optimize field management practices for crop growth under different climate conditions [29–31]. This model also performed well in simulating crop growth and soil water content under different deficit irrigation conditions [32–35]. Li et al. [36] and Fang et al. [37] reported that the RZWQM2 was appropriate for simulating crop growth and yield under deficit strategies. Liu et al. [38] and Cheng et al. [39] used the RZWQM2 to simulate the effects of long-term management practices on crop yields. However, fewer studies have been conducted to optimize irrigation practices for cotton yield using long-term climate and RZWQM2 under an extremely arid environment. Chen et al. [40] developed a new decision support system for irrigation scheduling (DSSIS) based on the S water stress by RZWQM2, which was calibrated and validated by Liu et al. [2]. A reasonably accurate simulation of crop yield and soil water content (θ) by RZWQM2 was found at a cotton field [40].

A previous study performed preliminary calibration of the model based on the θ, phenological stages and cotton yield. However, the S crop water stress by RZWQM2 was closely related to crop growth and measured (M) transpiration (T) in DSSIS. Thus, the performance of RZWQM2 in simulating cotton growth and T in arid region need to be evaluated under deficit irrigation. The objectives of this study were to: (i) calibrate RZWQM2 using DSSIS; and (ii) evaluate long-term (1990–2019) different irrigation practices on IWUE and cotton seed yield using the calibrated RZWQM2 model in northwest China.

2. Materials and Methods

2.1. Decision Support System for Irrigation Scheduling (DSSIS)

DSSIS is an automated irrigation control system, which combined with RZWQM2, four-day weather forecasts and an automatic irrigation control hardware and pipeline system offers state-of-the-art control over the timing and quantity of irrigation applied to a given crop. In DSSIS, the crop water stress (SWFAC < 0.9) S by RZWQM2 is used to determine the irrigation time for the full irrigation treatment. Current day weather information, four-day weather forecasts, the S current volumetric soil water content (θ) and field capacity are used to calculate the irrigation amount in DSSIS under full irrigation. The mode of calculation of SWFAC, as S by RZWQM2, and of the irrigation amount, determined in DSSIS, can be found in Qi et al. [34] and Chen et al. [41], respectively. Details on the development of this DSSIS was reported by Gu et al. [42] and Chen et al. [40].

2.2. Field Experiments

The field experiments were conducted over four growing seasons, from 2016 to 2019, at the Cele National Station of Observation and Research for Desert–Grassland Ecosystem, Chinese Academy of Sciences (37.02° N, 80.73° E). Weather data (daily minimum and maximum air temperature, shortwave radiation, wind speed, relative humidity, and rainfall) from 2016 to 2019 were recorded at the Cele National Station of Observation and Research for Desert–Grassland Ecosystem weather station (51826) located within 20 m from site the experimental field (Figure 1). Historical meteorological data from 1990 to 2015 were downloaded from the China Meteorological Data Sharing Services System (CMDSSS, http://data.cma.cn/ accessed on 18 April 2020). The average daily growing season (April to October) temperature and rainfall were 20.6 °C and 49 mm in 2016–2019, respectively, and 22.8 °C and 56 mm in 1990–2019. The soil texture is a fine sand. The M bulk density and soil texture were based on the study of Liu et al. [2].

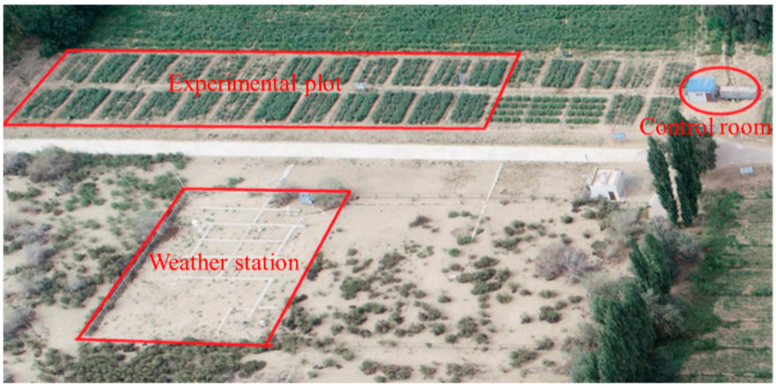

Figure 1. Overview of the layout experimental plot.

Two irrigation levels (full and deficit irrigation) were implemented under the DSSIS, with four replicates laid out in a randomized block design across two adjoining fields. Each plot was 10 m × 6 m, north–south and east–west, respectively. The widely planted 'Xinluzao No. 779' cotton cultivar, was planted in N/S rows. Seeds were over sown manually at an average rate of 222,000 seeds ha^{-1}, with a 0.1 m row spacing and 0.04 m planting depth. Prior to planting, a drip irrigation system was installed under a transparent polyethylene film mulch and sheep manure was applied at a rate of 240 kg N ha^{-1}. Details regarding experimental field management can be found in Chen et al. [41].

2.3. Field Measurements

An array of soil moisture temperature sensors (Dalian Qifeng Technology Co., Ltd., Dalian, China, SMTS–II–485) were served to monitor T°_{soil} at depths of 0.10 m, 0.20 m, 0.30 m, 0.50 m and 0.80 m. From planting to harvest, the volumetric θ at soil profile depths of 0–0.15 m, 0.15–0.25 m, 0.25–0.40 m, 0.40–0.65 m and 0.65–1.00 m soil layers was M weekly by the oven-dry method. In 2017–2018, the leaf area and plant height of plants randomly selected from each plot were M by Image J soft and steel ruler, respectively. The leaf area index (LAI) was estimated from the M leaf area and experimental plot area. From July to September and for each irrigation treatment a representative cotton plant was randomly selected for measurement of daily M *T*. The probe of a Flow32–1K (Dynamax Co., Ltd., Torrington, CT, USA) device was installed on the cotton stem 0.15 m from the ground. A 0.15 W of power was applied to the stem through a 12 mm wide thin resistive heater. The entire meter was wrapped in reflective aluminum foam film approximately 10 mm thick and 40 mm long. Use a data logger-multiplexer unit to sample the meter signal every 60 s and calculate a 60 min average for storage. Attributable to topsoil T°_{soil} > 50 °C, outliers among the M *T* values were removed (sandy soil heats up quickly and the probe was close to the ground). The *T* of cotton was estimated based on the plot area and the number of cotton plants. Mean daily *T* (g/h), was determined from flow measurements on plants by normalizing the stem flow data on a leaf area basis. The detailed calculation method can be found in a reference to Ham et al. [43]. Before harvest, three randomly chosen and representative cotton plants were sampled to measure aboveground biomass after oven-drying. Cotton seed yield was M by manually harvesting all plants in each plot.

2.4. RZWQM2 Description and Simulations

RZWQM2 includes the main modules that address physical (hydrology and heat), chemical, carbon and nitrogen cycle, pesticide transport and transformation, crop growth and field management [44]. The present study focuses on the physical and crop growth modules. The RZWQM2 model can simulate the effect of different agricultural management protocols on soil moisture and heat and crop growth. In the present paper, DSSIS–based full irrigation was used to calibrate the model with respect to θ, crop yield and aboveground biomass of cotton for the 2016–2019 seasons, and plant height and leaf area index for the 2017–2018 seasons. The DSSIS-based deficit irrigation was used to validate the RZWQM2 model against the same state variables. The model runs were performed continuously over the whole investigation period without re-initialization. Soil hydraulic parameters and crop parameters of RZWQM2 were calibrated by trial and error method. The calibrated soil hydraulic parameters and crop development parameters for cotton cultivar are shown in Tables 1 and 2, respectively.

Table 1. The M bulk density, soil texture, and calibrated soil hydraulic parameters for experimental sites at the Cele National Station of Observation and Research for Desert–Grassland Ecosystems.

Soil Depth (m)	ρ (Mg m^{-3})	Soil Texture			k_{sat} (mm h^{-1})	p_b (mm)	Soil Moisture Content at Different Matric Potentials				
		Sand (%)	Silt (%)	Clay (%)			θ_{sat} Ψ_m = 0	θ_{fc*} Ψ_m = −10 kPa	θ_{fc} Ψ_m = −33 kPa	θ_{pwp} Ψ_m = −1500 kPa	θ_r $\Psi_m = -\infty$
0–0.15	1.40	66.1	25	8.9	52.3	−136.5	0.45	0.20	0.13	0.05	0.03
0.15–0.30	1.45	65.4	27.7	6.9	23.4	−136.5	0.45	0.20	0.13	0.05	0.05
0.30–0.60	1.45	64.8	25.6	9.6	49.8	−136.5	0.45	0.20	0.13	0.05	0.04
0.60–0.90	1.48	67.6	24.5	7.9	47.0	−136.5	0.45	0.20	0.13	0.05	0.05
0.90–1.20	1.43	65.8	24.1	0.1	55.0	−136.5	0.45	0.20	0.13	0.05	0.05
1.20–1.50	1.43	65.8	24.1	0.1	52.5	−136.5	0.45	0.19	0.13	0.05	0.05
1.50–1.78	1.43	65.8	24.1	0.1	52.2	−136.5	0.45	0.19	0.13	0.05	0.05

Note: ρ is bulk density; k_{sat} is saturated soil hydraulic conductivity (mm h^{-1}); pb is bubbling pressure; θ_{sat} is saturated soil moisture content; θ_{fc*} is soil moisture at field capacity, sandy soil; θ_{fc} is soil moisture at field capacity, standard soil, θ_{pwp} is soil moisture content at permanent wilting point; θ_r is residual water content.

2.5. Irrigation Scenario and Economic Analysis

To optimize irrigation scheduling for this region, 30 years (1990–2019) of cotton yields and IWUE were S under different irrigation levels using the calibrated and validated RZWQM2. Seven irrigation totals per growing season levels were tested: Irr850 (850 mm), Irr750 (750 mm), Irr700 (700 mm), Irr650 (650 mm), Irr550 (550 mm), Irr450 (450 mm), and Irr350 (350 mm) treatments.

Table 2. Calibrated crop development parameters for 'Xinluzao No. 779′ cotton cultivar.

Parameter	Description	Value
EM–FL	Time between plant emergence and flower appearance (days)	35
FL–SH	Time between first flower and first pod (days)	11
FL–SD	Time between first flower and first seed (days)	17
SD–PM	Time between first seed and physiological maturity (days)	25
FL–LF	Time between first flower and end of leaf expansion (days)	51
LFMAX	Maximum leaf photosynthesis rate at 30 °C, 350 vpm CO_2, and highlight (mg CO_2 m^{-2} s^{-1})	1.1
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm^2 g^{-1})	180
SIZLF	Maximum size of full leaf (cm^2)	200
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.85
WTPSD	Maximum weight per seed (g)	0.2
SFDUR	Seed filling duration for pod cohort at standard growth conditions (days)	18
SDPDV	Average seeds per pod under standard growing conditions (seeds pod^{-1})	22
PODUR	Time required for cultivar to reach final pod load under optimal conditions (days)	8

The irrigation amount under Irr650 represents the multi-year average of standard local irrigation practice, while other treatments were increased or decreased based on the Irr650 treatment. An average interval of 15 days (irrigation interval of local farmers) was set to the conventional irrigation time (Irr650) for 1990–2019. All treatments received a pre-sowing irrigation of 150 mm. Six irrigation events were scheduled per growing season. Planting and harvest dates were set at 11 April (average planting date of the 2006–2015 field experiments) and at maturity (100% open bolls), respectively, over 30 years. The IWUE for each year was calculated by the ratio of cotton seed yield to the sum of irrigation and rainfall.

An economic analysis was conducted based on the S average cotton yield and irrigation amount for each treatment over 30 years. These economics components included gross and net income (\$ ha^{-1}), water cost (\$ ha^{-1}) and net water production (Nwp, \$ m^{-3}). Water cost was calculated based on irrigation amount and irrigation water price, and Nwp was the rate of net income to irrigation amount. Basic costs were estimated to be \$2000 ha^{-1} for each treatment, including fertilizers, seeds, weeding, planting, and harvest. Water (0.04 \$ m^{-3}) and cotton prices (1.3 \$ kg^{-1}) used for calculation were the average of local government pricing and local market pricing, respectively [41]. The average exchange rate of RMB to the \$ was 6.67 (2016–2018).

2.6. Model Performance Evaluation

To evaluate the model performance in comparison to M soil moisture and temperature, LAI, plant height, *T*, aboveground biomass and yield of cotton under plots with DSSIS-based irrigation with full and deficit irrigation, we adopted a number of the model accuracy statistics: root mean squared error (RMSE), relative root mean squared error (RRMSE), percent bias (PBIAS), and index of agreement (IOA). These statistical criteria are defined as follows:

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

$$\mathrm{RRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - M_i)^2}}{\overline{M}} \quad (2)$$

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n}(S_i - M_i) \times 100}{\sum_{i=1}^{n}(M_i)} \quad (3)$$

$$\mathrm{IOA} = 1 - \frac{\sum_{i=1}^{n}(S_i - M_i)^2}{\sum_{i=1}^{n}\left(\left|M_i - \overline{M}\right| + \left|S_i - \overline{M}\right|\right)^2} \quad (4)$$

where n is total number of items in the data set; S_i is the ith S value; M_i is the ith M value; $\overline{M}$ is the mean M value.

Model performance is considered acceptable if −30% < RRMSE < 30%, −15% < PBIAS < 15%, and IOA > 0.75 [45,46].

3. Results

3.1. Model Calibration for Full Irrigation

The S cotton seed yield and aboveground biomass in 2016–2019 are shown in Figure 2, and all the pertinent model accuracy statistics are shown in Table 3 (full irrigation). Average S cotton seed yield and aboveground biomass in the calibration phase for the full irrigation field were 4.51 Mg ha^{-1} and 11.42 Mg ha^{-1} over 4 years. The RMSE, RRMSE, PBIAS and IOA were 0.36 Mg ha^{-1}, 8%, 2.5% and 0.62 for the S cotton seed yield, and 1.49 Mg ha^{-1}, 12%, −5.9%, and 0.98 for the S aboveground biomass, respectively. A plot of the S and M LAI and plant height for the years 2017 and 2018 (Figure 3) indicates that over the two years, the LAI and plant height under full irrigation were S "satisfactorily" (IOA > 0.97). In the calibration phase, under full irrigation the RMSE, RRMSE, PBIAS and IOA values were, respectively, 0.61, 28%, 7.5% and 0.98 for the S maximum LAI, and 72 mm, 11%, 4.4%, and 0.99 for maximum plant height. Over 4 years, θ at different soil depths was S with acceptable accuracy by RZWQM2, except in the case of the for 0.45–1.00 m soil layer (Figure 4). In the calibration phase, the RMSE, RRMSE, PBIAS values for θ were <0.04 m^3 m^{-3}, 23 to 30%, −12 to 7%. The IOA value for θ in the 0–0.45 m soil layer was >0.7.

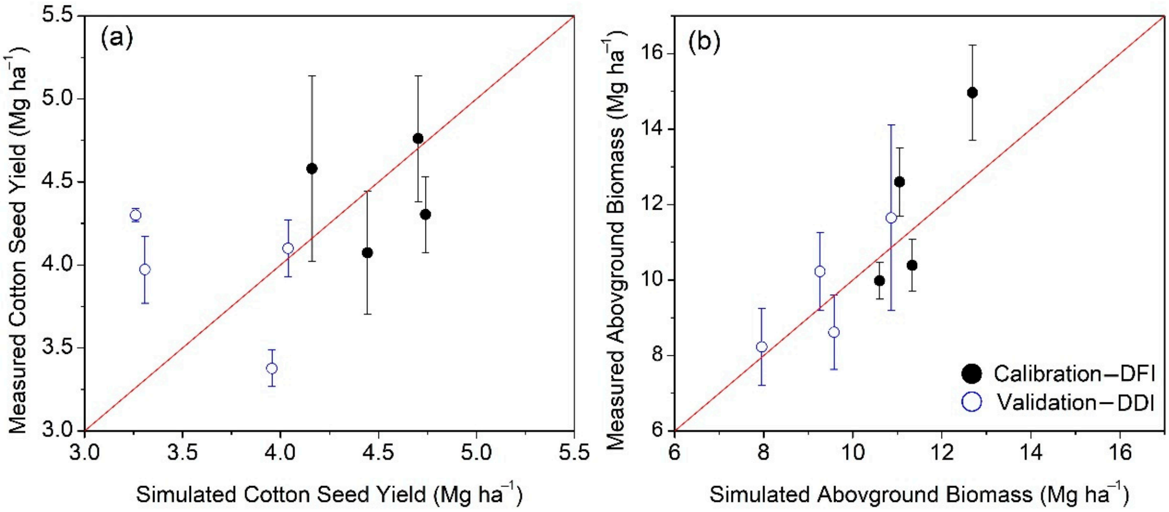

Figure 2. The simulated (S) versus measured (M) cotton seed yield (**a**) and aboveground biomass (**b**) under full and deficit irrigation in 2016–2019. DFI/DDI is the DSSIS under full/deficit irrigation.

Table 3. Statistics of comparison for the S versus M crop yield, aboveground biomass and maximum LAI, plant height, M transpiration (T), and θ and T°_{soil} for the calibration (full irrigation) and validation (deficit irrigation) phases.

Plant Parameters and Soil Parameters by Depth [a]		Calibration (Full Irrigation) [b]						Validation (Deficit Irrigation)					
		M	S	RMSE	RRMSE	PBIAS	IOA	M	S	RMSE	RRMSE	PBIAS	IOA
Plant parameters	Cotton yield (Mg ha^{-1})	4.43	4.51	0.36	8%	2.5%	0.62	3.38	3.64	0.68	20%	−10.3%	0.21
	Aboveground biomass (Mg ha^{-1})	11.98	11.42	1.49	12%	−5.9%	0.98	9.68	9.42	0.79	8%	−3.5%	0.99
	Maximum LAI	3.81	3.83	0.61	28%	7.5%	0.98	3.39	3.09	0.49	27%	0.7%	0.98
	Max. plant height (cm)	83	94	7.2	11%	4.4%	0.99	77	82	5.99	10%	3%	0.99
	Mean T (mm d^{-1})	4.2	3.4	1.1	27%	−18%	0.97	3.2	2.7	1.3	41%	14%	0.95
Soil water content, θ	θ (0–0.15 m)	0.111	0.114	0.032	29%	2.7%	0.82	0.106	0.099	0.035	30%	−6.3%	0.76
	θ (0.15–0.25 m)	0.128	0.112	0.042	30%	−12.3%	0.71	0.119	0.100	0.044	37%	−16.1%	0.65
	θ (0.25–0.45 m)	0.119	0.116	0.034	29%	−2.4%	0.73	0.109	0.104	0.038	35%	−5.0%	0.66
	θ (0.45–0.65 m)	0.129	0.128	0.034	26%	−1.3%	0.65	0.104	0.113	0.029	28%	8.8%	0.67
	θ (0.65–1.00 m)	0.127	0.136	0.030	23%	7.0%	0.53	0.105	0.111	0.027	25%	5.1%	0.55
Soil temperature, T°_{soil}	0–0.15 m	25.01	23.88	2.07	8%	−4.8%	0.91	25.00	23.27	2.78	11%	−7.5%	0.8
	0.15–0.25 m)	24.85	23.64	1.63	7%	−5.2%	0.92	24.96	24.14	2.57	10%	−3.5%	0.84
	(0.25–0.45 m)	24.76	23.42	1.70	7%	−5.8%	0.9	24.81	23.78	2.37	10%	−4.5%	0.83
	0.45–0.65 m)	24.34	22.96	1.60	7%	−6.1%	0.88	24.26	23.4	2.26	9%	−3.9%	0.8
	0.65–1.00 m)	23.45	22.16	1.45	6%	−6%	0.8	23.35	22.68	2.05	9%	−3.1%	0.74

[a] LAI = leaf area index, T°_{soil} = soil temperature (°C), θ = soil moisture content (cm^3 cm^{-3}). [b] M = measured average, S = simulated average, RMSE = root mean squared error, RRMSE = relative root mean squared error, PBIAS = percent bias, IOA = index of agreement.

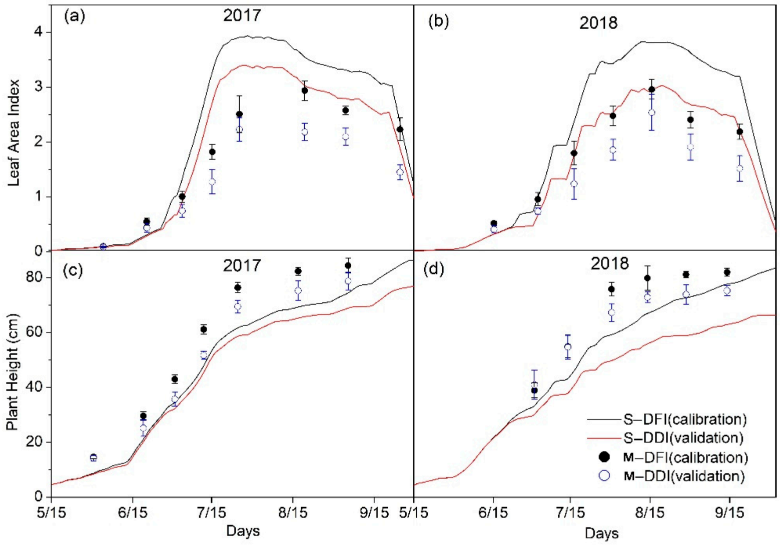

Figure 3. The S versus M leaf area index (**a**,**b**) and plant height (**c**,**d**) in 2017–2018 under DFI and DDI.

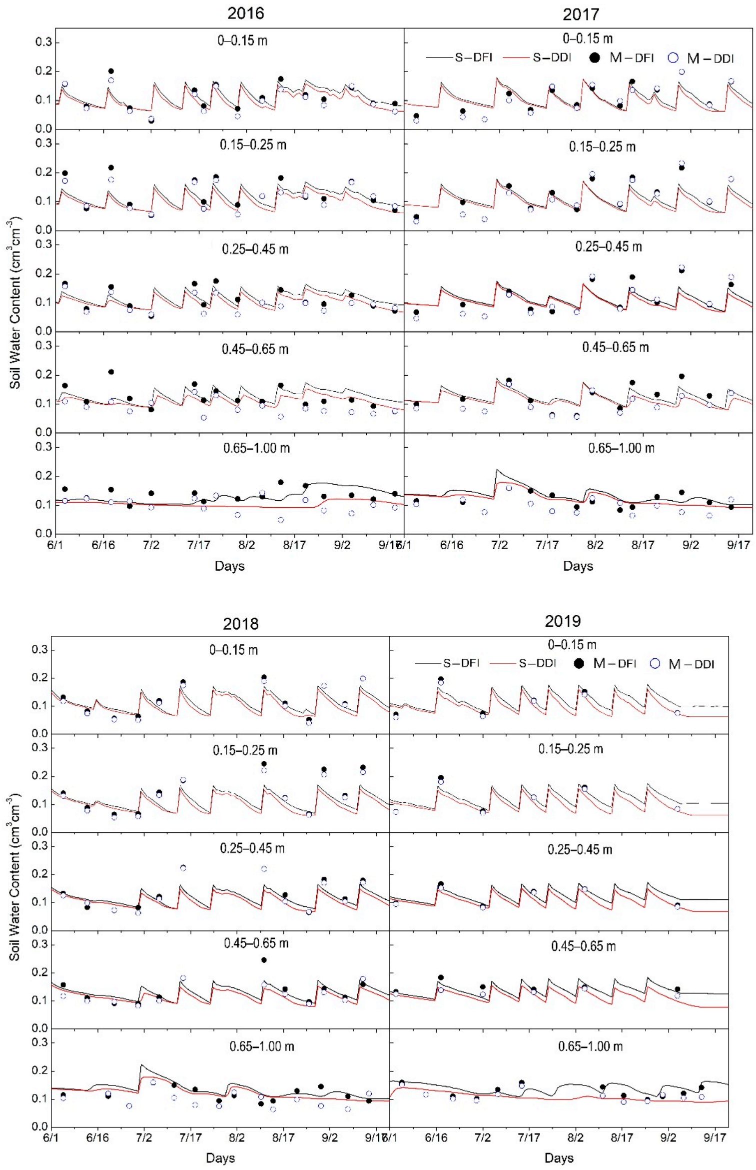

Figure 4. The S and M soil water content under DFI and DDI in 2016–2019.

3.2. Model Evaluations for Deficit Irrigation

The validation results showed the calibrated model to performed relatively well in simulating cotton yield, aboveground biomass, plant height and (0–0.65 m) in the deficit irrigation field (Table 3). In the validation phase, the model S a cotton yield of 3.64 Mg ha^{-1}, within 8% of the M yield of 3.38 Mg ha^{-1} (RMSE = 0.68 Mg ha^{-1}, RRMSE = 20%, PBIAS = −10.3% and IOA = 0.22). The RMSE, RRMSE, PBIAS and IOA values for aboveground biomass in the validation phase (deficit irrigation) were 0.79 Mg ha^{-1}, <15%, <30% and >0.9, respectively. The model slightly overestimated LAI and plant height for cotton in the validation phase. The accuracy of θ simulation in the validation phase varied from layer to layer, with depths below 0.65 m showing relatively inaccurate simulations (Figure 4). The validated RZWM2 model was considered to provide acceptable predictions of θ under deficit irrigation (Table 3). The S θ (0–0.15 m) in validation plots was within the range of the M values, with a RMSE = 0.035 m^3 m^{-3}, RRMSE = 30%, PBIAS = −6.3% and IOA = 0.76. The RZWQM2 S θ (0.15–1.00 m) relatively well under deficit irrigation (RMSE < 0.044 m^3 m^{-3}, RRMSE < 37%, −16.1% < PBIAS < 8.8%, and IOA > 0.55).

3.3. Soil Temperature Simulations

The S daily T°_{soil} for each layer under full and deficit irrigation treatments matched the M field data reasonably well (Figure 5). Averaged across the two years, the S average T°_{soil} (0–1.00 m) values for full and deficit irrigation were 23.2 °C and 23.5 °C, respectively, 1.3 °C and 1.02 °C lower than the M values. The RMSE for the S T°_{soil} was 1.5 °C to 2.1 °C and 2.1 °C to 2.8 °C under full irrigation and deficit irrigation, respectively. The RRMSE and PBIAS ranged from 6% to 11% and −7.5% to −3.5% under full and deficit irrigation, respectively (Table 3). For the full and deficit irrigation treatments, IOA > 0.8, except for the 0.65–1.00 m soil layer in the deficit irrigation field.

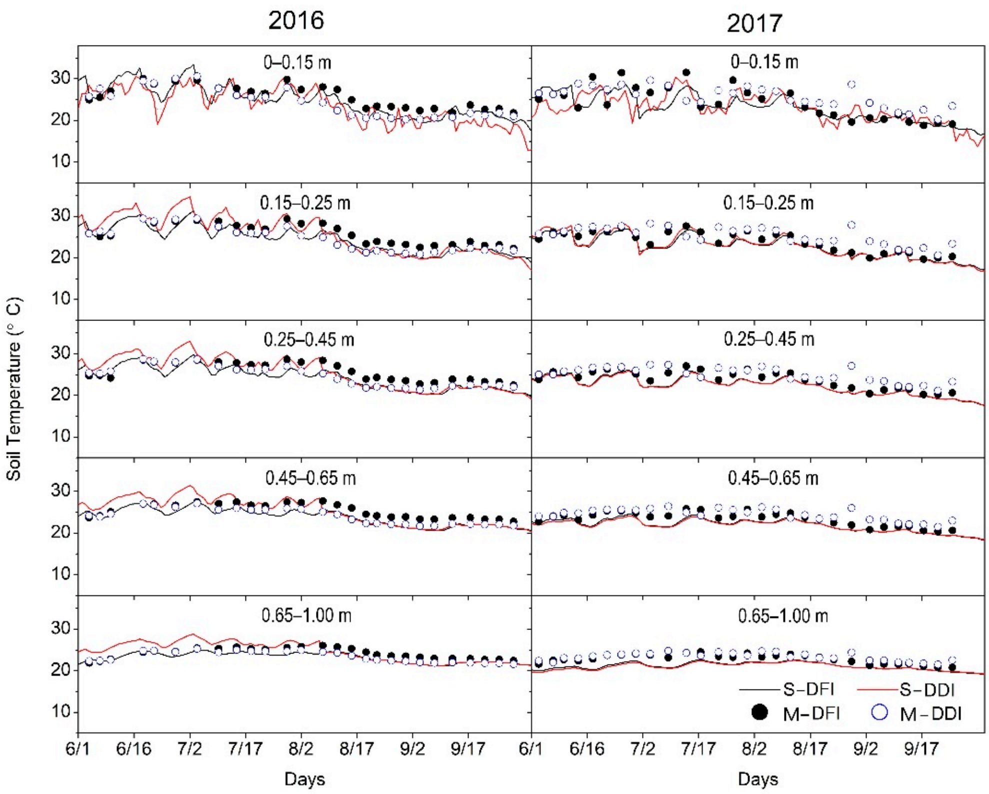

Figure 5. The S versus M soil temperature (T°_{soil}) under DFI and DDI in 2016–2017.

3.4. Cotton M vs. S T

The S cotton *T* under full and deficit irrigation was in a good agreement with the M (2018–2019) data. From July to September, under full irrigation, the S *T* ranged from 1.3 mm d^{-1} to 6.4 mm d^{-1}, while the M values ran from 1.4 mm d^{-1} to 5.6 mm d^{-1} (Figure 6). When averaged over the entire observation period (2018–2019), the average S *T* under full irrigation was 3.4 mm d^{-1}, namely a 0.8 mm d^{-1} (19%) lower value than was M (Table 3). The RMSE, RRMSE, PBIAS and IOA for *T* were 1.1 mm d^{-1}, 27%, −18% and 0.97. The average *T* for the deficit-irrigated field was 3.2 mm d^{-1}, with a 1.0 mm d^{-1} (32%) lower *T* than the fully irrigated field. Under deficit-irrigated conditions, the average *T* was 2.7 mm d^{-1} (1.1–5.6 mm d^{-1}) for the S values. The RZWQM2 S *T* relatively well under deficit irrigation (RMSE = 1.3 mm d^{-1}, RRMSE = 41%, PBIAS = 14%, IOA = 0.95).

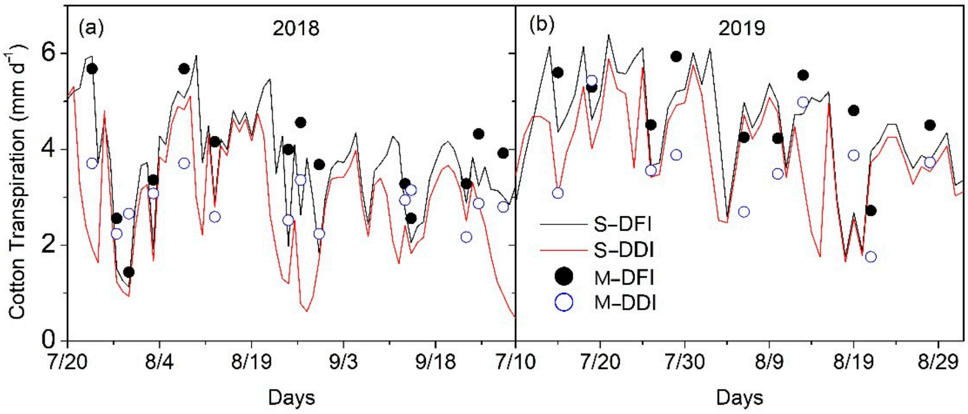

Figure 6. The S versus M cotton transpiration under DFI and DDI in 2018 (**a**) and 2019 (**b**).

3.5. Irrigation Scheduling Optimization (1990–2019)

Averaged across all irrigation treatments and across the period of 1990–2019, the S cotton seed yield and IWUE were 3.59 Mg ha^{-1} and 5.36 kg ha^{-1} mm^{-1}, respectively (Figure 7). In the present study, the maximum value for the S cotton seed yield was obtained under the Irr650 treatment, and the highest IWUE under the Irr550 treatment. The S 30-year average cotton yield under the Irr650 treatment was 4.09 Mg ha^{-1}, which was 5.9%, 2.9%, 1.5%, 1.8%, 26.4%, and 112.7% greater than that under Irr850, Irr750, Irr700, Irr550, Irr450, and Irr350 treatments, respectively. The maximum average IWUE (6.53 kg ha^{-1} mm^{-1}) was achieved with the Irr550 treatment, with a 54.4%, 33.7%, 23.8%, 14.1%, 4.3% and 41.6% greater value than the Irr850, Irr750, Irr700, Irr650, Irr450, and Irr350 treatments, respectively.

The results of the economic analysis showed that the Irr550 treatment provided the maximum Nwp, greater net income and lower water costs (Table 4). Water cost under the Irr550 treatment was \$132 ha^{-1}, which was 55%, 36%, 27% and 18% lower than the cost under Irr850, Irr750, Irr700 and Irr650 treatments, respectively. The maximum gross income was found under the Irr650 treatment (\$3165 ha^{-1}), followed by the Irr550 (\$3093 ha^{-1}) and Irr700 (\$3075 ha^{-1}) treatments. The Nwp value under Irr550 treatment was \$0.94 m^{-3}, which was 69%, 41%, 28%, 15%, 20%, and 371% greater than under The Irr850, Irr750, Irr700, Irr650, Irr450, and Irr350 treatments, respectively.

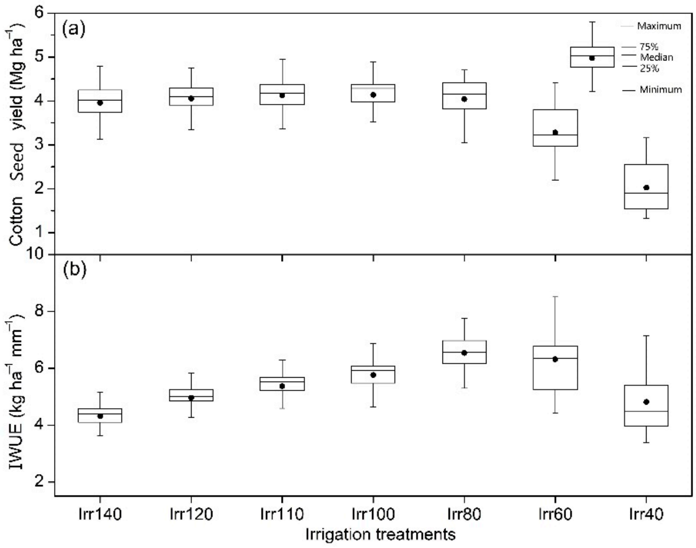

Figure 7. The S cotton seed yield (**a**) and IWUE (**b**) under different irrigation scheduling in 1990–2019.

Table 4. Economic analysis for different irrigation treatments.

Treatments	Yield Mg ha^{-1}	Irrigation m^3 ha^{-1}	Cotton Price $ kg^{-1}	Water Price $ m^{-3}	Gross Income $ ha^{-1}	Water Cost $ ha^{-1}	Basic Cost $ ha^{-1}	Net Income $ ha^{-1}	Nwp $ m^{-3}
Irr850	3.96	5100	0.04	1.3	5144	204	2000	2940	0.58
Irr750	4.05	4500	0.04	1.3	5271	180	2000	3091	0.69
Irr700	4.12	4200	0.04	1.3	5359	168	2000	3191	0.76
Irr650	4.14	3900	0.04	1.3	5380	156	2000	3224	0.83
Irr550	4.04	3300	0.04	1.3	5255	132	2000	3123	0.95
Irr450	3.28	2700	0.04	1.3	4267	108	2000	2159	0.80
Irr350	2.03	2100	0.04	1.3	2634	84	2000	550	0.26

Note: Nwp is the net water production value.

4. Discussion

The RZWQM2 was used to simulate θ and T°_{soil}, aboveground biomass and yield of cotton under drought conditions. The RZWQM2, a hybrid model between RZWQM and DSSAT4.0, successfully calculated cotton growth (aboveground biomass, LAI, and plant height) achieved in the field under a newly developed DSSIS providing either full or deficit irrigation. Thorp et al. [47] and Li et al. [36] reported that the DSSAT model could effectively simulate cotton growth processes (LAI, canopy height, and biomass) under various deficit irrigation conditions. In the present study, the RZWQM2 tended to slightly overestimate cotton seed yield and plant height achieved under the DSSIS for both full and deficit irrigation. The overestimation of cotton seed yield might be attributable to heavy winds and rainfall in 2016 during harvest stage and relatively lower seedling emergence rate in 2018, but not in cotton aboveground biomass and LAI. Positive biases in cotton growth and seed yield predictions may be severe enough to warrant any adjustment to model calibration to remove these biases. In addition, the modeled response of cotton yield to high water stress and temperature stress needs further investigation. Similar results were found by Thorp et al. [4] and Anapalli et al. [48] with irrigated cotton production in hot, arid Arizona (USA). In the current case, RZWQM2–S daily T was generally in good agreement with T M with the Flow32–1K equipment. Similarly, Qi et al. [34] and Sima et al. [35] demonstrated that the RZWQM2 S the crop ET well under full and deficit irrigation.

The RZWQM2 S θ and T°_{soil} well in the soil surface profile. These results concurred with those of Ma et al. [49] and Fang et al. [50] and Qi et al. [34]. Compared with the results of Chen et al. [40], evaluation parameters of the model for the S θ have been improved in this study. Compared to θ, Cheng et al. [39] reported that the RZWQM2–predicted T°_{soil} was in better agreement with the observed data. The present results for θ and T°_{soil} may be affected by the accuracy and position of soil moisture measurements, which was also noticed in other similar studies [51,52]. The model calibration results were slightly better than the validation results, which concurred with the results of Ding et al. [53] and Li et al. [36]. This may be the result of the relatively complex structure of the agricultural system model being S. In RZWQM2, the soil evaporation term of evapotranspiration is not added when considering water stress factors. Overall, post hoc the RZWQM2 simulations demonstrated a reasonable ability to accurately estimate θ and T°_{soil}, T, cotton growth and yield, showing acceptable levels of range.

Optimized irrigation strategies are essential to improving crop yield and IWUE in arid regions. Long-term (1990–2019) simulation results showed that the Irr550 treatment provided the highest IWUE (6.53 kg ha^{-1} mm^{-1}) and Nwp (0.94) under the region's current management practices. Based on a two–year field experiment, Shareef et al. [6] reported that irrigating cotton up to 80% of field capacity (832 mm) would provide the optimum yield and WUE (4.2 kg ha^{-1} mm^{-1}) in this region. In the current study, the S cotton yield under Irr850, Irr750 and Irr700 treatments were only slightly lower than under the Irr650 treatment. Annual rainfall over the period of 1990–2019 ranged from 11 mm to 224 mm. In years when rainfall > 80 mm, the amount of irrigation water applied under these treatments may exceed the cotton crop's water requirements, resulting in crop vegetative overgrowth. Using the Penman–Monteith model, Wang et al. [54] reported that the average cotton water requirement (1963–2012) in southern Xinjiang was 726–810 mm. Chen et al. [41] showed that DSSIS-controlled deficit (vs. full) irrigation led to a 3.55 kg ha^{-1} mm^{-1} (54%) decrease in WUE and 119 mm (21%) increase in the quantity of irrigation water applied. Based on a large-scale regional water–nitrogen model, Zhao [55] reported that the optimal growing season irrigation rate was 604 mm for southern Xinjiang, China. Similar estimates of an optimal irrigation rate (i.e., 400 mm to 600 mm) were also found in other studies undertaken in the region [56,57].

5. Conclusions

The performance of the RZWQM2 was evaluated against data collected from full and deficit irrigation cotton fields in Northwest China. The M results included θ and T°_{soil}, cotton growth (LAI, plant height, aboveground biomass), cotton actual transpiration and yield from 2016 to 2019. After model calibration and validation, the RZWQM2 proved to be capable of simulating θ and T°_{soil} in the surface profile in an acceptable manner for a region subject to drought conditions. The model performance was acceptable in terms of simulating crop growth and yield for deficit–irrigated cotton. The characteristics of actual transpiration in cotton plants under full and deficit irrigation was also analyzed using the calibrated RZWQM2. Therefore, RZWQM2 can be used to evaluate the response of cotton yield to different deficit irrigation practices under arid climate conditions. Long-term (1990–2019) simulation results showed that the traditional irrigation practices (Irr650 treatment) provided the highest cotton yield and net income. However, cotton producers would benefit, in terms of improving IWUE and increased Nwp, from using deficit irrigation (Irr550 treatment). Long-term impacts of water and nitrogen management practices on crop yield and nitrogen balance in a cotton field under extreme drought conditions will be S in the future.

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