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A Model-Based Real-Time Decision Support System for Irrigation Scheduling to Improve Water Productivity

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Abstract: A precisely timed irrigation schedule to match crop water demand is vital to improving water use efficiency in arid farmland. In this study, a real-time irrigation-scheduling infrastructure, Decision Support System for Irrigation Scheduling (DSSIS), based on water stresses predicted by an agro-hydrological model, was constructed and evaluated. The DSSIS employed the Root Zone Water Quality Model (RZWQM2) to predict crop water stresses and soil water content, which were used to trigger irrigation and calculate irrigation amount, respectively, along with forecasted rainfall. The new DSSIS was evaluated through a cotton field experiment in Xinjiang, China in 2016 and 2017. Three irrigation scheduling methods (DSSIS-based (D), soil moisture sensor-based (S), and conventional experience-based (E)), factorially combined with two irrigation rates (full irrigation (FI), and deficit irrigation (DI, 75% of FI)) were compared. The DSSIS significantly increased water productivity (WP) by 26% and 65.7%, compared to sensor-based and experience-based irrigation scheduling methods ($p < 0.05$), respectively. No significant difference was observed in WP between full and deficit irrigation treatments. In addition, the DSSIS showed economic advantage over sensor- and experience-based methods. Our results suggested that DSSIS is a promising tool for irrigation scheduling.

Keywords: irrigation decision support system; agro-hydrological model; RZWQM2; water stress; weather forecast

1. Introduction

Improving water use efficiency (WUE) has become an important strategy in dealing with drought in zones with limited water resources. The exploitation of available fresh water, especially groundwater resources, has seriously hindered sustainable agriculture development and even economic growth in arid and semi-arid regions. Modern technologies are helping to achieve efficient water use in these regions [1]. One of the major water users, agriculture, now faces intense competition from other major water users, especially the industrial sector [2]. As a country with an enormous agricultural sector, China has a large area of cultivated lands, including marginal agricultural lands. China's agricultural water use accounts for about 70% of its total water consumption. The relatively low crop yield and WUE in many regions is the result of unreasonable irrigation and fertilizer application rates [3,4]. In order to improve the utilization of limited water resources under a modern agricultural practice, an accurate and efficient water-saving irrigation decision support system is required.

Establishing an automatic irrigation system can substantially improve irrigation WUE and crop productivity [5–7]. Several irrigation Decision Support Systems (DSSs) have been developed [8–12] and used in agricultural water resource management to improve WUE. A DSS can successfully serve to develop irrigation scheduling based on real-time crop status information [13]. An accurate and efficient DSS should take many factors into consideration, including weather, crop type, soil water status, irrigation method, and application efficiency [14,15]. Therefore, accurate measurements of soil, plant, and environmental variables are particularly important. To characterize the water status of the plant and soil, real-time sensors are commonly used to determine irrigation timing and amount. For example, automatic irrigation systems have been implemented using tensiometers; however, tensiometers require recalibration [16], and their positioning greatly affects soil water matric potential measurements [17]. Moreover, these irrigation systems require intensive labor and expensive devices to monitor soil moisture (θ). In addition, their installation in the field can affect field operations, especially mechanized harvesting. Furthermore, due to field variability, accurate installation of tensiometers is imperative for them to be effective.

Weather is one of the key factors considered in estimating crop water requirements, so, in order to improve irrigation WUE, agronomists generally rely on information (daily temperature, reference evapotranspiration (ET), and precipitation) from weather stations to adjust irrigation schedules. For example, Car et al. [18] designed an irrigation system management system that implemented a mobile phone Short Messaging Service (SMS) to access weather forecasts; however, their ET-based irrigation scheduling and SMS system did not accurately reflect crop water deficit conditions.

A series of indices have been developed to optimize irrigation scheduling: indirect, external environmental factors, e.g., θ and meteorological conditions [19–22], and direct, crop physiological parameters, e.g., canopy temperature [23–25]. Indirect indicators such as θ may not reflect the crop's water deficit, whereas crop physiological indicators are more accurate in estimating crop water deficit. With multiple factors to be considered, irrigation scheduling merely based on θ measurements cannot accurately determine optimal irrigation timing and quantity. Crop water requirements are related to leaf area index (LAI), crop root growth, and upcoming weather conditions. At present, few irrigation scheduling DSSs draw on indirect (vs. direct) indicators to determine irrigation timing and quantity. Gao et al. [26] has developed a precision irrigation system based on crop water stresses measured by a wireless sensor network employing an acoustic emission technique. The use of sensors to monitor crop water status is a widely used method to study crop water stresses [27]. As a non-destructive method to monitor crop canopy temperature, the infrared thermometer has an additional advantage of producing low measurement errors in plant temperature [28]; however, this method to calculate crop water stresses usually requires a reference value of crop canopy temperature under full irrigation [29].

Crop models integrate various aspects of agricultural production systems and it may be used as a surrogate for irrigation scheduling. Thorp et al. [30] developed a prototype precision farming DSSs called Apollo using the Decision Support System for Agrotechnology Transfer (DSSAT) crop growth model. Likewise, a two-level optimization model incorporating the SWAP-EPIC agro-hydrological model was developed to maximize an irrigation system's WUE and economic returns [31]. While applying crop models directly to irrigation management and decision-making is rare, Thorp et al. [32] did report that the CSM-CROPGRO-Cotton model could provide appropriate in-season irrigation management recommendations. Crop models have also been applied as simulation tools to address a variety of research questions related to irrigation management under subsurface drip irrigation [33].

Agro-hydrological models and software (i.e., the Root Zone Water Quality Model (RZWQM)) have been widely applied to simulate crop responses to water stresses under various environmental scenarios, and to make irrigation decisions to alleviate crop water stresses. The RZWQM model has shown promise in simulating crop water and nutrient cycling [34,35], and in the evaluation of agricultural water resources utilization and ecosystem viability [36]. Using a Root Zone Water Quality Model (RZWQM2) (a later version of RZWQM), Saseendran et al. [37] tested the effectiveness of different water stress factors in RZWQM simulation of maize (*Zea mays* L.) under different irrigation conditions. Ma et al. [38] used the RZWQM2 model to predict maize yield under different deficit irrigation. Based on crop water stress simulated in the RZWQM model, Fang et al. [39] optimized irrigation strategies for a wheat–maize (*Triticum aestivum* L.–*Z. mays*) double cropping system on the North China Plain. Evaluating the accuracy of simulation of crop growth and water stress in eastern Colorado using the RZWQM2 model, Qi et al. [29] found the dates of water stress occurrence and the responses of crop yield to water stresses to be well simulated.

Based on the fact that RZWQM2 can adequately simulate water stresses under various environmental scenarios, Gu et al. [40] developed an irrigation scheduling software RZ_IrrSch based on the RZWQM2-predicted crop water stresses. The software was tested under two virtual scenarios: arid maize production in Colorado and a humid soybean (*Glycine max* (L.) Merr.) production in Mississippi of USA. However, the DSS has not been implemented or evaluated to schedule irrigation at a field site. This study constitutes an effort to combine this agro-hydrological model-based software and irrigation control hardware to construct a new Decision Support System for Irrigation Scheduling (DSSIS). As virtual tests suggested that the software would perform better under arid conditions, this new DSSIS system was constructed and assessed in an extremely dry cotton field in southern Xinjiang, China. The RZWQM2 model had been calibrated using data collected at an irrigated cotton (*Gossypium hirsutum* L.) site in this region from 2007–2014 by Liu et al. [41]. Therefore, the objective of this study was to test a new DSSIS in improving water productivity (WP) for irrigated cotton in a cotton field in Northwest China.

2. Materials and Methods

2.1. Root Zone Water Quality Model (RZWQM2)

The Root Zone Water Quality Model (RZWQM) is a 1D model housing physical, chemical, and biological processes for simulating agricultural management effects on soil processes, crop production, and water quality [42–44]. Agricultural management includes plant management (planting density, row spacing, planting depth, method of planting, time of harvest, type of harvest), irrigation management (type of irrigation, application rate, time, and amount of irrigation), and fertilizer management (methods of application, $NO3^-$-N, $NH4^+$-N, Urea-N amount). The RZWQM2 model incorporates DSSAT (Decision Support System for Agrotechnology Transfer) version 4.0 crop growth modules and the SHAW (Simultaneous Heat and Water) energy balance modules. The DSSAT model provides a database of cultivar parameters for the crops and cultivars simulated in the RZWQM2 model. The CSM-CROPGRO-COTTON model (DSSATv4.5), incorporated into RZWQM2 model, was used in this study. In RZWQM2, the potential evapotranspiration (PET) is estimated using the Shuttleworth–Wallace method, and actual root water uptake is derived from either the Nimah–Hanks equation when the generic plant growth module is invoked or from an empirical equation when the DSSAT crop growth modules are used.

2.2. Decision Support System for Irrigation Scheduling (DSSIS) Framework

As a key component of the newly developed decision support system for irrigation scheduling (DSSIS), the RZWQM2 model served as the engine in making irrigation scheduling decisions. The water stress factor calculated by the RZWQM2 model was used to set the timing of future irrigations. The amount of future irrigation under the DSSIS was estimated through the difference between soil field capacity θ_{fc} and simulated θ of the rooting layer, minus current and 4-day forecasted rainfall.

2.2.1. The DSSIS Framework Design

The DSSIS system is composed of two major parts, a core control software (IrrSch, version, Manufacturer, City, US State abbrev. if applicable, Country), and irrigation hardware. Having provided weather updates information to IrrSch software installed on a PC, the user can then send the irrigation command (irrigation time and amount) to irrigation control software through a network switchboard, which controls the irrigation valves and circulating pump. The DSSIS system includes four main components (Figure 1):

- Irrigation pipeline system, consisting of polyvinyl chloride (PVC) pipe, drip irrigation pipe, and valves. The drip irrigation pipes are equipped with pressure compensation type emitters with a flow rate of 5 Lh^{-1} at a pressure of 1–2 bar. The distance between two emitters is 0.1 m to match the plant spacing.
- Irrigation control software, consisting of weather data acquisition (online for the future and site-specific for current), RZWQM2 model, and IrrSch decision and control software. The development of this IrrSch software can be found in Gu et al. [40]. The system functions as follows:
    - The RZWQM2 model, with crop and soil parameters calibrated using a historical field experiment from 2007–2014 [41], is installed on a PC;
    - The IrrSch software retrieves current day weather information from an on-site weather station as well as 4-day weather forecasts from a weather Application Program Interface (API) (http://api.openweathermap.org), and subsequently feeds into RZWQM2;
    - RZWQM2 is called by IrrSch and executed to predict the water stress factor, crop ET, and θ for the current and four upcoming days;
    - When the current day's predicted water stress factor is less than a user defined threshold, an irrigation event is triggered and the amount of water to be supplied is calculated using the θ_{fc}, the predicted current θ, the predicted crop rooting depth, and the total amount of current and forecast 4-day rainfall.
- Irrigation control hardware, consisting of soil moisture sensors, electromagnetic valves, the field programmable logic controller (F-PLC), the site of programmable logic controller (S-PLC), frequency conversion controller (FCC), and the user operating the S-PLC to facilitate irrigation;
- Peripheral equipment, consisting of a reservoir, circulating pump, strainer, and groundwater pumping station, to secure a water supply for crops.

2.2.2. The Network Information Transfer in the DSSIS

The developed DSSIS used an agricultural management information network (Figure 2) to control information flow in the system. The network switchboard control system consisted of the spot irrigation control room, the F-PLC, and meteorology station. The user imports weather information to the computer located in the spot irrigation control room through a network switchboard, relying on the IrrSch software to send the irrigation command to the S-PLC through a Single Chip Microcomputer (SCM). The system will implement an irrigation event when the electromagnetic valve and the FCC receive the irrigation command from the computer. The FCC controls the start or stop of pumping. In order for the user to see variations in θ in a convenient and timely manner, the F-PLC receives and feeds back information on θ to the S-PLC's touch screen.

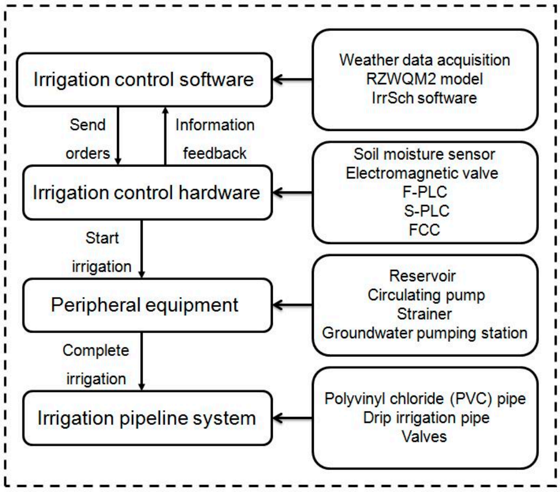

Figure 1. The Decision Support System for Irrigation Scheduling (DSSIS) based on Root Zone Water Quality Model (RZWQM2) predicted water stress factor and weather forecasts. F-PLC, the field programmable logic controller; S-PLC, the site of programmable logic controller; FCC, frequency conversion controller.

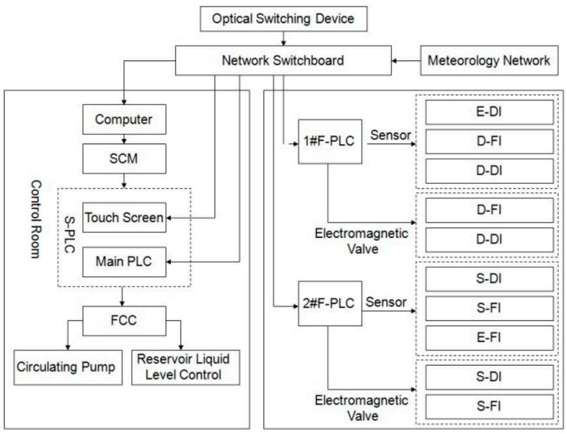

Figure 2. Network structure of Decision Support System for Irrigation Scheduling (DSSIS). SCM, Single Chip Microcomputer; PLC, programmable logic controller; S-PLC, the site of programmable logic controller; FCC, frequency conversion controller. D-FI and D-DI, the DSSIS system using an RZWQM2 model simulated water stress under full irrigation and deficit irrigation; S-FI and S-DI, sensor–based full irrigation and deficit irrigation; E-FI and E-DI, experience-based full irrigation and deficit irrigation.

2.3. Irrigation Control Software

2.3.1. Information Acquisition

Using the water stresses calculated by RZWQM2 to determine the timing of irrigation is one of the key features of the DSSIS, but applying the right amount of irrigation water to achieve the most efficient use of water is equally important for any irrigation system. Another feature of the DSSIS is that the quantity of irrigation applied is determined using θ_{fc}, the predicted current θ, the simulated crop rooting depth, and the total amount of current and forecast 4-day rainfall. The meteorological data includes the daily minimum and maximum temperature, shortwave radiation, wind speed, relative humidity, and rainfall. Since the format of automatically downloaded weather data is incompatible with the format of RZWQM2 input files, it was necessary to establish a MySQL database to reformat the weather information. Subsequently, weather data were fed into RZWQM2 by initiating the IrrSch software from the MySQL database. The user could then make a timely decision regarding irrigation based on the simulated water stresses, the water deficit, and the estimated irrigation amount for the next four days.

2.3.2. Irrigation Schedule Software

The IrrSch software is composed of two main interfaces:

- The first interface (Figure 3) hosts seven steps through which users can input basic information into the software. Steps 1 through 6 include entering previously calibrated and validated information regarding RZWQM2 model parameters [41]. Because some parameters (planting density, tillage, etc.) do not need to be updated annually, users simply update the planting date. The seventh step includes three subroutines, but the user only controls two of these:
    - the "Update Weather Data" button to read the weather data files which have been downloaded from the weather station;
    - the "Calculation" button to run the RZWQM2 model and for the IrrSch to enter the second interface.
- The second interface is the irrigation operations interface (Figure 4), which serves to view the information regarding water stress and crop growth, and provides users with the ability to send an irrigation instruction to the SCM. On this interface, the "Calculate" button may be used to update the value of soil water stress factor (SWFAC, 0 = extreme stress and 1 = no stress), root depth and irrigation amount and timing, as well as rainfall and crop biomass. If the value of water stress factor is less than 0.9, users must input an irrigation amount and time by pressing the "+" button. In other words, irrigation will not be triggered if SWFAC > 0.9. The suggested maximum single irrigation amount is presented in the tables of the second interface. The "Send to SCM" button will send irrigation instructions to the S-PLC and activate the FCC controlled circulating pump. The whole irrigation management operation may be automated to promote the adoption and commercialization of this newly developed irrigation management system. Root length is determined within RZWQM by simulated root growth in each soil layer.

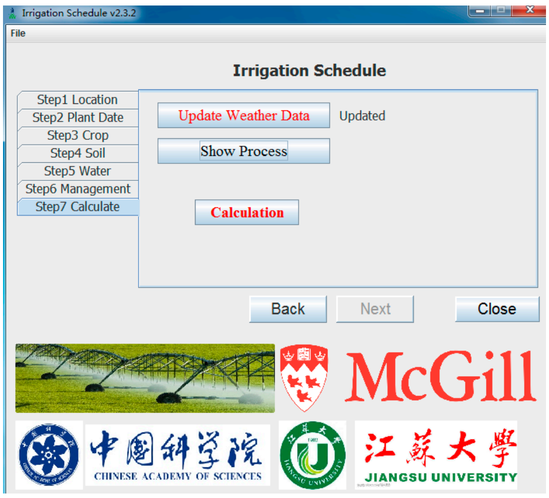

Figure 3. Main interface of IrrSch software.

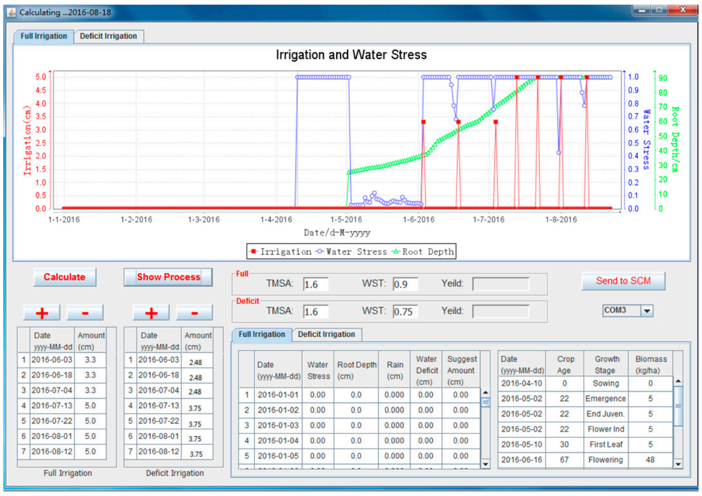

Figure 4. Second user operation interface of IrrSch software.

2.3.3. The Water Stress Factor Algorithm in DSSIS

The soil water stress factor (SWFAC) calculated by the RZWQM2 model represents the extent to which θ across the rooting depth cannot meet crop transpiration. SWFAC is used to calculate photosynthesis and other elements of the dry matter accumulation processes, and thus provides a good indication of water deficit. Accordingly, irrigation was triggered when SWFAC dropped below 0.9. The specific calculation of SWFAC in the DSSIS includes three steps: (1) the soil parameters and initial θ as inputs into the RZWQM2 model, (2) weather data downloaded from an onsite weather station (current day) and from a weather API (next 4 days), and (3) RZWQM2 simulated daily crop growth (biomass and leaf area index, etc.) as well as potential transpiration (T_p) and actual crop water uptake. The formula for SWFAC is given as [45]:

$$\mathrm{SWFAC} = \frac{\sum \mathrm{RWU(L)} \times \mathrm{RLV(L)} \times \Delta \mathrm{L}}{\mathrm{T_P}}, \tag{1}$$

$$\mathrm{RWU(L)} = \frac{\mathrm{k_1} \times \mathrm{e}^{\mathrm{k_2} \times [\mathrm{SW(L)} - \mathrm{LL(L)}]}}{\mathrm{k_3} - \ln[\mathrm{RLV(L)}]}, \tag{2}$$

$$\mathrm{T_p} = \frac{\Delta[(\mathrm{R_n} - \mathrm{G}) - \mathrm{R_{nsub}}] + \frac{\rho \times \mathrm{c_p} \times \mathrm{VPD_0}}{\gamma_a^c}}{\Delta + \gamma\left(1 + \frac{\gamma_s^c}{\gamma_a^c}\right)}, \tag{3}$$

where

c_p—volumetric heat capacity of air (MJ m^{-3} °C^{-1}),
k_1, k_2 and k_3—dimensionless constants drawn from DSSAT, v3.5: $k_1 = 1.32 \times 10^{-3}$, $k_2 = 120 - [250 \times LL(L)]$, and $k_3 = 7.01$.
G—heat flux below the canopy (MJ m^{-2}),
$LL(L)$—lower limit of plant-available water in the soil layer (cm^3 cm^{-3}),
R_n—net radiation above the canopy (MJ m^{-2}),
R_{nsub}—net radiation over the bare soil and residue (MJ m^{-2}),
$RWU(L)$—potential root uptake per unit root length for soil layer L (cm^{3}watercm^{-3} root),
$RLV(L)$—root length density in the soil layer (cm root cm^{-3} soil),
$SW(L)$—current soil water content in the soil layer (cm^3 cm^{-3}),
T_p—potential transpiration (cm), calculated using the Shuttleworth–Wallace equation,
VPD_0—air vapor pressure deficit at the mean canopy height (kPa),
γ_a^c—bulk boundary layer resistance of the canopy elements within the canopy (s m^{-1}),

γ_s^c—bulk stomatal resistance of the canopy (s m^{-1}),
γ—the psychrometric constant (kPa °C^{-1}),
ρ—the density of air (kg m^{-3}),
Δ —slope of the saturation vapor press versus temperature curve (kPa °C^{-1}),
ΔL—the depth of the soil layer (cm).

2.4. Irrigation Control Hardware

2.4.1. The F-PLC Design

The F-PLC (Figure 5) has two main functions: (1) controlling the electromagnetic valves by receiving computer instructions, (2) receiving the information from the soil moisture sensor and sending the information to S-PLC through the network switchboard. The F-PLC is composed of an air switch, fuse protector, wire connector, PLC (Siemens SIMATIC S7-200 SMART, Beijing, China), relay, soil moisture sensors, and electromagnetic valves. The soil moisture sensors (Dalian Qifeng Technology Co. Ltd., China, SMTS-II-485) used an RS-485, MODBUS-RTU protocol for their output signal. The sensor served to monitor θ and soil temperature based on frequency domain reflectometry (FDR) measurements taken at two-second intervals. The measurement accuracy of θ and soil temperature were 3% and 0.4 °C, respectively. The soil moisture sensors were calibrated prior to installation.

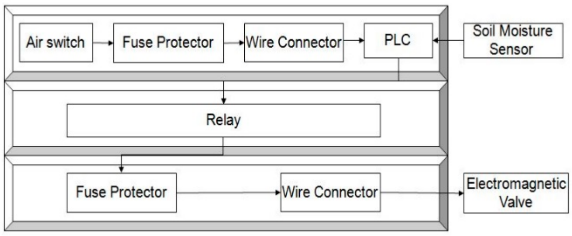

Figure 5. Design chart of the F-PLC employed in this study. PLC, programmable logic controller.

2.4.2. The S-PLC Design

The S-PLC (Figure 6) also had two main functions:

- to provide a touch screen for the user to implement irrigation events by controlling the electromagnetic valves and view real-time information on θ, and
- to control the F-PLC, which controls the circulating pump. The S-PLC mainly includes a touch screen (SIEMENS SMART LINE), PLC, and power source box.

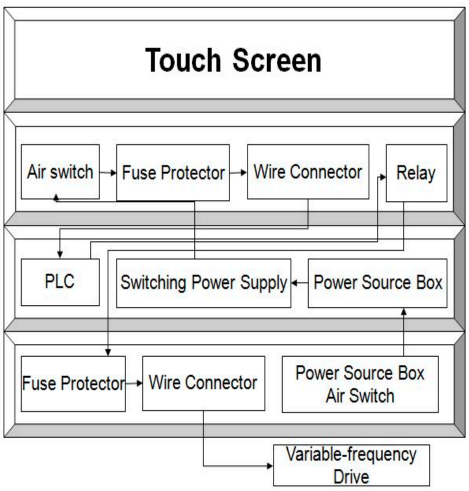

Figure 6. Design chart of the S-PLC employed in this study. PLC, programmable logic controller.

The touch screen:

- to monitor real time variation in θ for each plot in order to set an appropriate irrigation threshold under the desired irrigation regime, and to control the irrigation system for that plot, and
- to select manual or rotation irrigation mode.

2.4.3. The FCC Design

The main function of the FCC (Figure 7) is to ensure the equipment smoothly, reduce energy consumption, adjust the running frequency of the equipment, and reduce the damage to the motor caused by the large current when the device is started. The FCC is made up of operation buttons, a frequency converter (JTE 320S-D), a liquid level transistor relay (JYB-714), an alternating current contactor, a fuse protector, a relay, an air switch, a wire connector, and a terminal block.

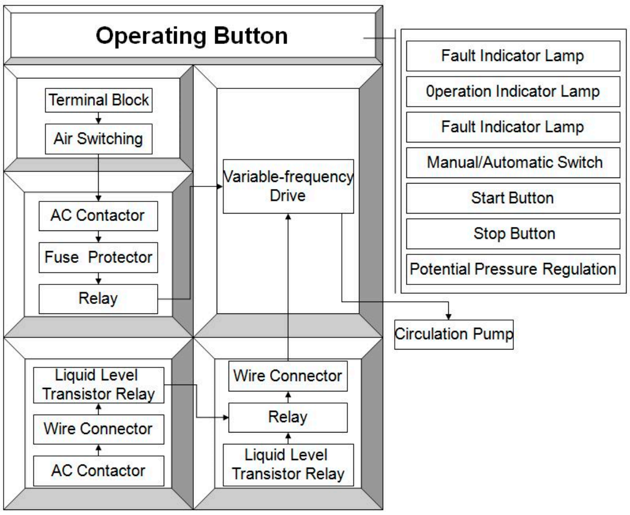

Figure 7. Design chart of the FCC employed in this study. AC Contactor, Alternating Current Contactor.

2.5. Experimental Site

The infrastructure of the DSSIS, sensor- and experience-based irrigation system was constructed in March 2016 at the Cele National Station of Observation & Research for Desert-Grassland Ecosystem, Chinese Academy of Sciences (37°01′06′′ N, 80°43′48′′ E) in the Qira Oasis of southern Xinjiang, China (Supplement Figure S1). To evaluate the effectiveness of the DSSIS, it was compared with other two irrigation scheduling methods relying on soil moisture sensors and conventional experience-based approaches, respectively, all factorially combined with either full (FI) or deficit irrigation (DI, 75% of FI). The experiment has been conducted since April 2016, and, in this study, two years of data are reported (2016 and 2017). The experimental field area covered an area of 0.144 ha in a fine sand soil. Weather data were recorded at the Cele National Station of Observation & Research for Desert-Grassland Ecosystems weather station (51826) near the test site (Figure 8). The field was divided into 24 experimental plots, each 10 m long (N/S) and 6 m wide (E/W), arranged in two sets of twelve plots, 2 m apart, arrayed on either side of the E–W running irrigation mains (Figure 9). Each plot was randomly assigned one of 24 ($3 \times 2 \times 4$) irrigation scheduling× irrigation amount × replicate combinations. On 10 April 2016 and 19 April 2017, cotton (*G. hirsutum* cv. 'Xinluzao No. 779′) was planted in N/S rows at a 0.1 m row spacing and average rate of 222,000 seeds ha^{-1}. Cotton was harvested on 23 September 2016 and 28 September 2017. Sheep manure was applied at planting at a rate of 240 kg N ha^{-1}, and fertilizer supplemented throughout the growing season according to plant growth and fertilizer uptake estimated through experience. Prior to sowing, each plot was covered with three 1.25 m wide bands of plastic mulch (0.6 m apart), each bearing two drip lines. The average soil bulk density was measured to be 1.32, 1.32, 1.34, 1.36, and 1.16 g cm^{-3} for the 0–0.15 m, 0.15–0.25 m, 0.25–0.40 m, 0.40–0.65 m, and 0.65–1.0 m soil layers, respectively.

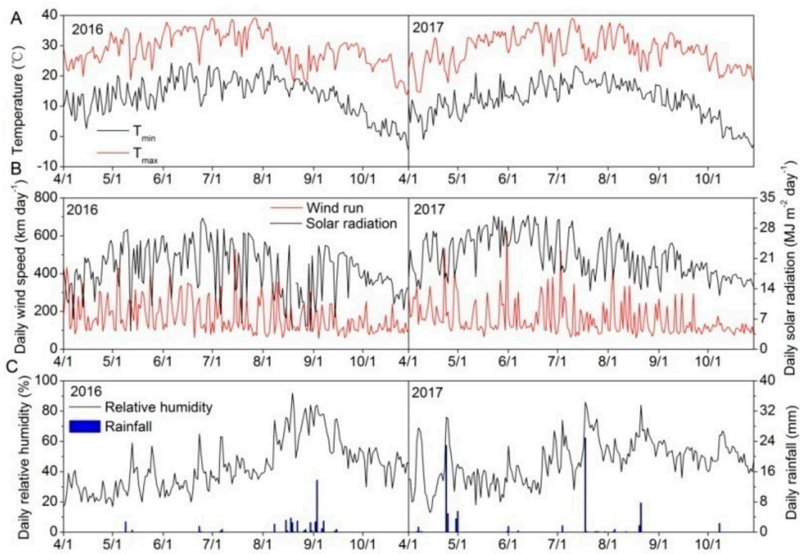

Figure 8. Daily maximum and minimum temperature (**A**), wind speed and solar radiation (**B**), relative humidity and rainfall (**C**) at the experimental site during the cotton growing period (April–October) in 2016 and 2017.

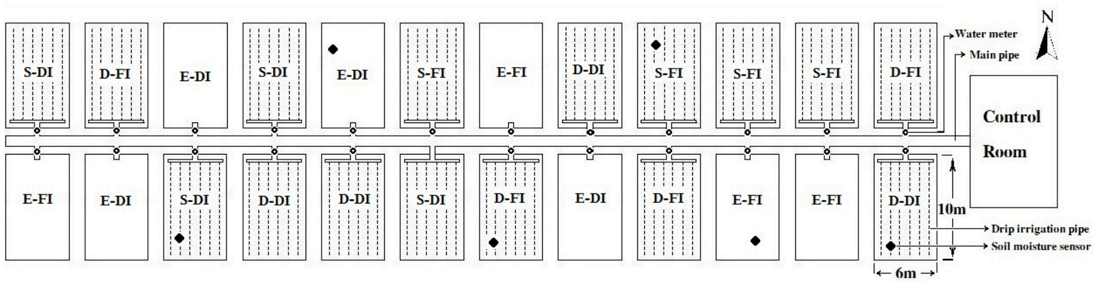

Figure 9. Layout of the experimental plots. D-FI and D-DI, the DSSIS system using RZWQM2 model simulated water stress under full irrigation and deficit irrigation; S-FI and S-DI, sensor–based full irrigation and deficit irrigation; E-FI and E-DI, experience–based full irrigation and deficit irrigation.

2.6. Irrigation Treatment Design

The field experiment followed a completely randomized 3 × 2 factorial design with four replicates. One factor was irrigation scheduling, including:

- the DSSIS system using RZWQM2 model simulated water stress factor (D), soil moisture sensor (S), and experience (E).
- The other factor is irrigation amount, including full (FI) and deficit (DI, 75% of full) irrigation.

Water meters were used in each plot to ensure precise irrigation amounts when the value of SWFAC fell below a threshold of 0.9. Based on the difference between the θ_{fc} and current simulated θ, the depth of irrigation to be applied was calculated with IrrSch software [40], developed in Java language under the Eclipse platform. For the soil moisture sensor-based method, the irrigation event was triggered when the soil moisture sensors installed in the first soil layer reached a threshold of 0.06 cm^3 cm^{-3} and the full irrigation amount was calculated based on measured θ and θ_{fc} set at 0.15 cm^3 cm^{-3}. In the present study, the soil type is fine sand. The upper and lower thresholds of the sensor-based irrigation scheduling method were based on the literature [46], where it was reported that the total amount of water available for plant uptake called "plant available water" (PAW) ranged from

0.14 to 0.03 cm^3cm^{-3} in sandy soils. Haley and Dukes [47] set the irrigation threshold of sensor-based method at 0.07 cm^3cm^{-3} in a fine sand. In order to meet crop water demand and achieve water savings, we set the irrigated lower threshold of sensor-based full irrigation to 0.06 cm^3cm^{-3} at 0.10 m and irrigated upper threshold of sensor-based full irrigation to 0.15 cm^3cm^{-3} at 0.20 m. For the conventional experience-based method, the irrigation timing and amount followed the schedule of a neighboring cotton field managed by field technicians (Table 1).

Table 1. Experimental treatments imposed.

Treatment	Basis of Irrigation	Measurement	Irrigation Threshold	
			Start	Stop
D-FI	RZWQM2 model	SWFAC *	SWFAC < 0.9	θ_{fc}
D-DI	RZWQM2 model	SWFAC	Same as D-FI	75% of D-FI
S-FI	Soil moisture	Field-measured θ	$\theta_{0–0.1\ m}$ = 0.06 $cm^3\ cm^{-3}$	$\theta_{0–0.2\ m}$ = 0.15 $cm^3\ cm^{-3}$
S-DI	Soil moisture	Field-measured θ	Same as S-FI	75% of S-FI
E-FI	Experience	Visual/tactile	Grower's experience	θ_{fc}
E-DI	Experience	Visual/Tactile	Same as E-FI	75% of E-FI

* RZWQM2 simulated water stress factor (see Equation (1)): SWFAC = 1 indicates that there is no water stress; SWFAC < 1 indicates some water stress; SWFAC = 0 indicates maximum water stress. D-FI and D-DI, the DSSIS system using RZWQM2 model simulated water stress under full and deficit irrigation; S-FI and SDI, sensor-based under full and deficit irrigation; E-FI and E-DI, experience-based under full and deficit irrigation. θ, soil water content.

2.7. Yield, Water Productivity (WP), and Soil Water Content

Seed cotton yield was measured by manually harvesting all plants in each plot. Grain yield was computed using the seed cotton yield multiplied by the seed to fiber ratio. The seed to fiber ratio was measured using 500 lint samples from D-FI and D-DI plots. In each experimental plot, θ was monitored with soil moisture sensors buried at depths of 0.1, 0.2, 0.3, 0.5, and 0.8 m, representing the θ in soil layers of 0–0.15 m, 0.15–0.25 m, 0.25–0.40 m, 0.40–0.65 m, and 0.65–1.0 m, respectively. In addition, during the pre-irrigation and post-harvest periods, soil samples were collected in each experimental plot at weekly intervals, at the same soil depths near the cotton roots. The collected soil samples were placed in an oven at 105 °C for two days and dried to constant weight in the laboratory. The measured θ was compared with each layer's simulated θ. The water productivity (WP) was defined as the ratio of seed cotton yield to the sum of irrigation and precipitation water depths over the full growing season:

$$\mathrm{WP} = \frac{\mathrm{Y}}{(\mathrm{I} + \mathrm{P})}, \tag{4}$$

where

WP—irrigation water use efficiency (kg m^{-3}),
Y—seed cotton yield (kg m^{-2}),
I—the irrigation amount (m),
P—precipitation (m).

2.8. Statistical and Economic Analysis

The effects of the irrigation scheduling and irrigation levels on crop yield, total irrigation amount, and water productivity (WP) were analyzed using the PROC ANOVA procedure of SAS 9.2 software (Manufacturer, City, US State abbrev. if applicable, Country). Differences between means were examined at a probability level of 0.05 using Duncan's multiple range test. The irrigation scheduling × amount interaction was not significant ($p > 0.05$) for crop yield, total irrigation amount, or WP.

To evaluate the RZWQM2 model performance in simulating θ, the mean difference (MD), coefficient of determination (R^2), Nash–Sutcliffe model efficiency ($\mathbf{E_{NS}}$), and root mean squared error (RMSE) were used to evaluate the goodness of fit between simulated and measured values. The ratio of the MD to the measured mean is defined as the relative MD. Given the wide range of datasets involved, it is difficult to select a model performance criterion that would address all sources of inaccuracy; however, for simplicity, model performance was considered satisfactorily when $\mathbf{E_{NS}} \geq 0.5$ [29]. For yield prediction, only the MD was used since yield was only measured at harvest.

An economic analysis was conducted based on the assumption that the infrastructure for each irrigation scheduling was applied to a 10-ha cotton field, an average size of a drip irrigation farm in this area, with a 10-year operational lifetime. Labor cost was set at $50 per person for operating each irrigation event, and water and cotton price at $0.04 m^{-3} and $1.30 kg^{-1}, respectively, according to Shareef et al. [48] Fertilizer, seed and machinery was estimated $1500 ha^{-1} y^{-1}, the same for all irrigation scheduling methods.

3. Results and Discussion

3.1. Effectiveness of Irrigation Scheduling Methods

Statistical analyses of the effect of irrigation scheduling and irrigation quantity on seed cotton yield, total irrigation amount, and WP showed that the DSSIS method had an obvious advantage by increasing seed cotton yield, reducing total irrigation, and enhancing WP (Table 2). Averaged across both full and deficit irrigation strategies, two-year mean seed cotton yield was 4.44 Mg ha^{-1} under the DSSIS method, about 1.04 Mg ha^{-1} (30.5%) and 0.73 Mg ha^{-1} (19.4%) greater ($p \leq 0.05$) than yields under sensor-based and experience-based irrigation (3.40 Mg ha^{-1} and 3.72 Mg ha^{-1}), respectively. The 2-year averaged total seasonal irrigation under both the DSSIS and sensor-based irrigation scheduling methods (316 mm) was significantly lower (31.7% and 33.6%, respectively) than that under experience-based irrigation (476 mm). The 2-year mean WP under the DSSIS method was 1.16 kg m^{-3}, 0.24 kg m^{-3} (26%, $p \leq 0.05$) greater than that under the sensor-based method and 0.46 kg m^{-3} (65.7%, $p \leq 0.05$) greater than that under the experience-based method. With respect to full vs. deficit irrigation strategies, the average total irrigation over two years under deficit irrigation (320 mm) was roughly 75% of that under full irrigation (424 mm), suggesting that the equipment functioned well as designed thereby saving 25% of water ($p \leq 0.05$). Mean seed cotton yield under full irrigation was 4.19 Mg ha^{-1}, significantly greater (by 0.67 Mg ha^{-1} or 19%) than that under deficit irrigation (3.52 Mg ha^{-1}). In contrast, the 2-year mean WP under full irrigation (0.95 kg m^{-3}) was only 5.2% greater than under deficit irrigation (0.90 kg m^{-3}), an insignificant difference ($p > 0.05$). In general, the DSSIS method with irrigation triggered by model predicted water stresses performed significantly better than sensor-and experience-based methods.

Table 2. Crop yield, total irrigation amount, and WP as affected by two treatment factors.

Factors	Seed Cotton Yield (Mg ha^{-1})			Total Irrigation Amount (mm)			WP (kg m^{-3})		
	2016	2017	Average	2016	2017	Average	2016	2017	Average
Irrigation Scheduling									
DSSIS (D)	4.44	4.43	4.44A	324	326	325B	1.23	1.10	1.16A
Sensor (S)	4.00	2.80	3.40B	429	204	316B	0.86	0.98	0.92B
Experience (E)	3.40	4.02	3.71AB	481	471	476A	0.66	0.74	0.70C
Irrigation amount									
Full (FI)	4.16	4.21	4.19a	470	378	424a	0.84	0.96	0.95a
Deficit (DI)	3.74	3.29	3.52b	353	289	320b	0.98	0.91	0.90a

Means in each column followed by different letters indicates significant difference ($p \leq 0.05$). Capital letters for irrigation scheduling and lowercase letters for irrigation amount. DSSIS, Decision Support System for Irrigation Scheduling; WP, water productivity.

Statistical analyses across the six treatments showed that the DSSIS model-based method with deficit irrigation (D-DI) was the best overall choice (Table 3). There was no significant decrease in the 2-year mean seed cotton yield under D-DI compared to other treatments. Compared to D-FI, D-DI reduced the total of irrigation amount by 85 mm (23.2%) with only a small and non-significant decrease in seed cotton yield (0.47 Mg ha^{-1} or 10.1%). Compared to the E-FI irrigation practice commonly implemented in the region, D-DI not only saved about 48% irrigation water (282 mm vs. 543 mm) but also increased seed cotton yield by 4% (4.20 Mg ha^{-1} vs. 4.04 Mg ha^{-1}) and WP by 85.1% (1.24 kg m^{-3} vs. 0.67 kg m^{-3}). Compared to the S-DI treatment's seed cotton yield of 2.96 Mg ha^{-1}, D-DI provided a yield increase of 42% ($p \leq 0.05$), and a WP increase of 40.9% ($p \leq 0.05$) in spite of an increase in water use of 4.4% ($p \leq 0.05$).

Table 3. Crop yield, total irrigation amount, and WP under different irrigation treatments.

Treatments	Seed Cotton Yield (Mg ha^{-1})			Total Irrigation Amount (mm)			WP (kg m^{-3})		
	2016	2017	Average	2016	2017	Average	2016	2017	Average
D-FI	4.58	4.76	4.67a	370	365	368c	1.11	1.07	1.09ab
D-DI	4.30	4.10	4.20ab	278	287	282d	1.35	1.13	1.24a
S-FI	4.28	3.41	3.84abc	490	234	362c	0.80	1.09	0.95bc
S-DI	3.73	2.19	2.96c	368	173	270e	0.91	0.87	0.89bcd
E-FI	3.61	4.47	4.04abc	550	537	543a	0.61	0.73	0.67d
E-DI	3.20	3.58	3.39bc	413	405	409b	0.70	0.74	0.72cd

Means in each column followed by different letters indicates significant difference ($p \leq 0.05$).

The better cotton performance under DSSIS could be attributed to its greater irrigation frequency, which relieved crop water stress in a timely manner. The D-FI treatment triggered irrigation 6–9 times with an irrigation interval of 12.5 days on average for the two years. Comparatively, S-FI treatment triggered irrigation 4–7 times with an irrigation interval of 16.5 days on average over the two years. The experience-based method resulted in only 5–6 irrigation events with an interval of 16.5 days on average over the two years. Generally, a method of high frequency and low quantity per irrigation was the best strategy for shallow root plant growth. However, in the desert region where this study was undertaken, owing to the limited irrigation water and increasing competition between irrigation districts for water, high frequency irrigation intervals are not feasible. In addition, cotton is a drought-tolerant plant and some studies have reported that drip irrigation intervals should be set at a week or 15 days [49–52].

Over the two years, the response of water stress factor and measured θ to irrigation events triggered in the D-FI treatment are shown in Figure 10A. Owing to the increase in rooting depth of cotton under this treatment, the 2-year mean irrigation depth over the reproductive stage (July to August) was 200 mm greater than that at the vegetative stage (May to June). Crop water requirements were low at the vegetative stage due to less radiation energy or vapor deficit to drive ET. However, because of the timely irrigation, the water stress simulated by RZWQM2 was alleviated and the crop recovered from the very short time period of water stress (1–2 days). The soil water content and irrigation event for the S-FI and E-FI treatments over two years are depicted in Figure 10B,C, respectively. The decrease in irrigation amount under DSSIS-based method (vs. experience-based method) might be attributable to a decrease in ET or soil water content. DSSIS can fill the soil profile to satisfy the crop transpiration (Figure 10A). There was very little rainfall in this region (Qira Oasis), and rainfall did not exceed 2.0 cm each time. Therefore, the projected rainfall has little effect on actual irrigation in DSSIS in this region. However, no matter how much the forecasted rainfall is, the minimum irrigation amount applied would always be more than 3.0 cm in this study. Even though the actual rainfall might be less than the predicted rainfall, the water stresses could be removed owing to the fact that irrigation amount exceeds 3.0 cm each time. In other words, the water stresses will be detected earlier, and another irrigation will be triggered when current rainfall is less than the forecasted ones.

The poorer performance of sensor-based irrigation scheduling method may be related to field operation and irrigation threshold. Irrigation events were triggered when θ reached 0.06 cm^3 cm^{-3} in May and June, but, later, due to broken sensors in 2016, no water was applied at the locations where the sensors were installed. Instead, irrigation water was applied every two weeks in order to maintain crop growth. This malfunction demonstrated that the DSSIS was less affected by field operation than the sensor-based irrigation scheduling. The significant decrease in cotton yield under sensor-based (vs.

DSSIS-based) irrigation scheduling in 2017 might be attributed to the low threshold of θ set for the sensors, which resulted in a lower amount of irrigation water applied. Based on the literature [46,47], we set the irrigation threshold to 0.06 cm^3cm^{-3} for the fine sand in the study. The external environment, such as weather condition or field operation, may not be the main factor. However, a fixed upper and lower irrigation threshold values may be the main factor, which leads to a low irrigation amount for sensor-based method. In our study, the sensor-based irrigation scheduling method used a fixed upper and lower threshold to maintain the soil water content in the root soil layer. In fact, water stress may occur at different soil water content during the crop growth season. Sensor accuracy and installed position may also affect irrigation time and amount for sensor-based irrigation scheduling.

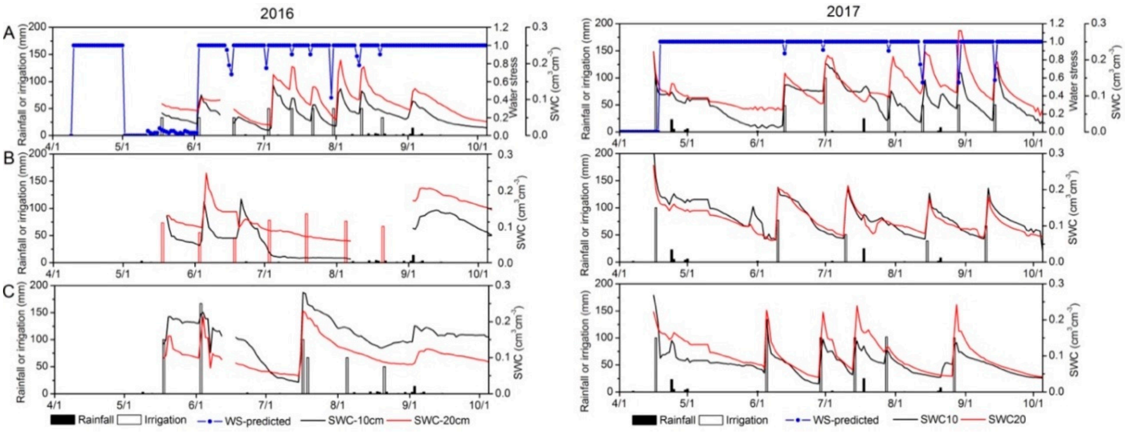

Figure 10. The water stress response to irrigation and rainfall in the D-FI treatment in 2016 and 2017 (**A**); soil water content response to irrigation and rainfall in the S-FI treatment in 2016 and 2017 (**B**); and soil water content response to irrigation and rainfall in the E-FI treatment in 2016 and 2017 (**C**). WS-predicted, predicted water stress; SWC, soil water content; SWC—0.10 m and SWC—0.20 m, soil water content monitored by sensor in 0.10 m and 0.20 m soil profile, respectively.

The economic analysis showed that the DSSIS in general achieved the highest net profit, with an assumption that the infrastructure of each method was applied to a 10-ha field with a 10-year operational lifetime (Supplement Table S1). The total investment for the infrastructure of DSSIS, sensor-, and experience-based methods were \$449, \$389 and \$0 ha^{-1} y^{-1}. The experience-based method was more labor intensive, with two working days for each irrigation event, while it was one working day for the DSSIS and sensor-based. The number irrigation events in each year were 7, 5, and 5 for the DSSIS, sensor-, and experience-based methods, and therefore the labor salary were \$350, \$250, and \$500 for those three methods, respectively. Water bills were \$130, \$126, and \$190 ha^{-1} y^{-1}, according to the irrigation amount in Table 2. Taking the \$1500 investment on fertilizer, seed, and machinery into account, the total cost for DSSIS, sensor-, and experience-based methods were \$2429, \$2265, and \$2190 ha^{-1} y^{-1}, while the total revenue from cotton sale were \$5772, \$4420, and \$4823 ha^{-1} y^{-1} based on the observed yield, respectively. Therefore, the net profit for DSSIS, sensor- and experience-based irrigation control methods were \$3343, \$2155, and \$2633 ha^{-1} y^{-1}, respectively.

3.2. Simulated and Measured Grain Yield and the Soil Moisture

The better performance of the DSSIS method can be attributed to a reasonably accurate simulation of crop yield and θ by RZWQM2. The simulated and measured grain yield, θ for each layer and soil water storage for the whole soil profile over two years are shown in Table 4. Simulated average grain yield under D-FI was 3.40 Mg ha^{-1}, within 16.8% of the measured value of 2.91 Mg ha^{-1}, while simulated average grain yield under D-DI was 2.44 Mg ha^{-1}, within 2.1% of the measured value of 2.39 Mg ha^{-1}.

Table 4. Statistics of comparison for simulated versus measured crop yield and soil moisture over two years for full irrigation (D-FI) and deficit irrigation (D-DI).

Parameter [a]	Full Irrigation [b]						Deficit Irrigation [b]					
	Sim.	Obs.	MD	E_{NS}	R^2	RMSE	Sim.	Obs.	MD	E_{NS}	R^2	RMSE
2016–2017												
Grain yield (Mg ha^{-1})	3.40	2.91	0.49	—	—	—	2.44	2.39	0.05	—	—	—
θ (0.05–0.15 m)	0.13	0.13	0.006	0.55	0.61	0.033	0.12	0.12	−0.002	0.69	0.69	0.031
θ (0.15–0.25 m)	0.13	0.12	0.003	0.85	0.79	0.023	0.12	0.12	−0.004	0.60	0.62	0.031
θ (0.25–0.40 m)	0.13	0.12	0.012	0.65	0.71	0.030	0.10	0.10	−0.001	0.46	0.47	0.030
θ (0.40–0.65 m)	0.11	0.12	−0.008	−0.04	0.19	0.037	0.08	0.10	−0.014	−0.17	0.12	0.032
θ (0.65–1.00 m)	0.10	0.11	−0.013	0.12	0.39	0.024	0.09	0.09	−0.003	0.19	0.20	0.203
SWS (0–1.00 m)	10.86	10.29	0.572	0.48	0.60	1.879	8.85	9.25	−0.407	0.48	0.51	1.896

[a] θ = soil water content (cm^{3}cm^{-3}), SWS = soil water storage (cm). [b] Sim. = simulated mean, Obs. = measured mean, MD = mean difference, E_{NS} = Nash-Sutcliffe model efficiency, R^2 = coefficient of determination, and RMSE = root mean squared error.

Except for the 0.40–0.65 m and 0.65–1.00 m soil layers, the RZWQM2 model adequately simulated the θ for each layer across the entire soil profile, both for full irrigation treatments ($E_{NS} \geq 0.65$; 0.023 m^3 m^{-3} ≤ RMSE ≤ 0.033 m^3 m^{-3}; and $0.61 \leq R^2 \leq 0.79$) and deficit irrigation treatments ($E_{NS} \geq 0.46$; 0.030 m^3 m^{-3} ≤ RMSE ≤ 0.031 m^3 m^{-3}; and $0.46 \leq R^2 \leq 0.69$) (Table 4, Figure 11). The soil water storage for both the full and deficit irrigation in the 0–1.0 m soil profile was simulated by the RZWQM2 model in an acceptable manner ($E_{NS} \geq 0.48$; $R^2 \geq 0.51$–Table 4, Figure 11). Although the model did poorly for the 0.40–0.65 m and 0.65–1.0 m soil layers under full irrigation and deficit irrigation, the model performance on simulatingθ in this study was comparable to other studies with RZWQM2 [29,53].

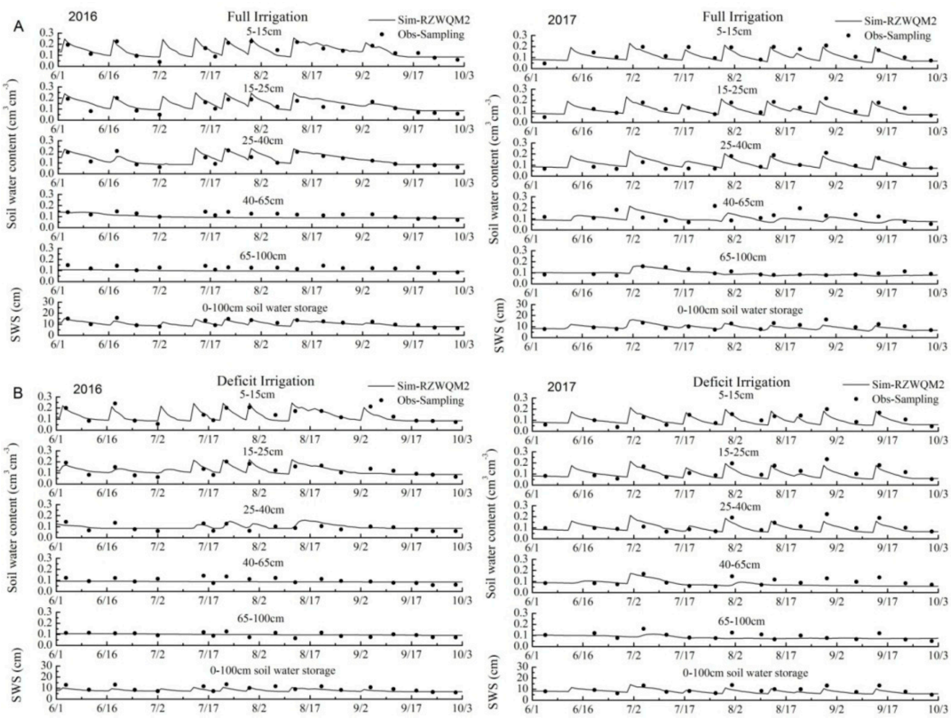

Figure 11. Simulated and measured soil water content for the full irrigation field (**A**) and deficit irrigation field (**B**) based on DSSIS in 2016 and 2017.

4. Conclusions

To alleviate the water crisis and improve water productivity (WP) in irrigated agriculture, a Decision Support System for Irrigation Scheduling (DSSIS) was tested in a case study wherein it was compared, under both full and deficit irrigation, with soil moisture sensor and conventional experience-based irrigation scheduling. The DSSIS, using model-predicted real-time water stress as a threshold to trigger irrigation, performed the best with the highest WP, the highest cotton yield, and a significant reduction in total irrigation amount compared to the experience-based method. Use of DSSIS under deficit irrigation saved the greatest amount of irrigation water (approximately 50%), increased yield by 4.0%, and enhanced WP by 80.6% compared to experience-based full irrigation. DSSIS is the most cost-effective according to the economic analysis. This study concluded that, given its ability to improve WP and to enhance economic return, the DSSIS is a promising infrastructure for real-time irrigation scheduling. Combined with deficit irrigation the DSSIS might be the best choice for farmers in the area under study. Further studies are needed to evaluate the effectiveness of DSSIS under other climate conditions and cropping systems.

Supplementary Materials: The following are available online at http://www.mdpi.com/2073-4395/9/11/686/s1, Figure S1.: Field experiment facilities, Table S1.: Economic analysis of the newly developed DSSIS applied to a 10-ha field with a 10-year operational lifetime.

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