Optimizing water-saving irrigation schemes for rice (*Oryza sativa* L.) using DSSAT-CERES-Rice model

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Abstract: Rice is one of the major crops in China, and enhancing the rice yield and water use efficiency is critical to ensuring food security in China. Determining how to optimize a scientific and efficient irrigation and drainage scheme by combining existing technology is currently a hot topic. Crop growth models can be used to assess actual or proposed water management regimes intended to increase water use efficiency and mitigate water shortages. In this study, a CERES-Rice model was calibrated and validated using a two-year field experiment. Four irrigation and drainage treatments were designed for the experiment: alternate wetting and drying (AWD), controlled drainage (CD), controlled irrigation and drainage for a low water level (CID1), and controlled irrigation and drainage for a high water level (CID2). According to the indicators normalized root mean square error (NRMSE) and index of agreement (*d*), the calibrated CERES-Rice model accurately predicted grain yield (NRMSE=6.67%, *d*=0.77), , shoot biomass (NRMSE=3.37%, *d*=0.77), actual evapotranspiration (ET_a) (NRMSE=3.83%, *d*=0.74), irrigation volume (NRMSE=15.56%, *d*=0.94), and leaf area index (NRMSE=9.69%, *d*=0.98) over 2 a. The calibrated model was subsequently used to evaluate rice production in response to the four treatments (AWD, CD, CID1, and CID2) under 60 meteorological scenarios which were divided into wet years (22 a), normal years (16 a), and dry years (22 a). Results showed that the yield of AWD was the largest among four treatments in different hydrological years. Relative to that of AWD, the yield of CD, CID1, and CID2 were respectively reduced by 5.7%, 2.6%, 8.7% in wet years, 9.2%, 2.3%, 8.6% in normal years, and 9.2%, 3.8%, 3.9% in dry years. However, rainwater use efficiency and irrigation water use efficiency were the greatest for CID2 in different hydrological years. The entropy-weighting TOPSIS model was used to optimize the four water-saving irrigation schemes in terms of water-saving, labor-saving and high-yield, based on the simulation results of the CERES-Rice model in the past 60 a. These results showed that CID1 and AWD were optimal in the wet years, CID1 and CID2 were optimal in the normal and dry years. These results may provide a strong scientific basis for the optimization of water-saving irrigation technology for rice.

Keywords: CERES-Rice, controlled irrigation and drainage, water-saving, long-term weather data, water use efficiency
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1 Introduction

Rice (*Oryza sativa* L.) is one of the most important cereal crops in the world. More than half of the world's population depends on rice as their staple food[1]. According to the National Bureau of Statistics of China's statistics for rice production from 2009 to 2020, China's average annual rice planting area and total production had reached 30.4 million hm^2 and 20.7 billion t, respectively. The planting area and total production were ranked first in the world[2]. Irrigated rice production is the largest consumer of water in the agricultural sector, and its sustainability is increasingly threatened by water shortages[3]. To address this growing problem, approaches must be found that decrease irrigation water demand while maintaining a high grain yield of rice. Various water-saving technologies such as inadequate irrigation[1] and alternate wetting and drying (AWD)[4] have been developed to lower the water consumption of rice crop. AWD has produced good results in rice fields, but rainwater use efficiency (RWUE) in AWD has been founded to be inadequate because the depth of ponding rainwater in rice paddies is low[5]. Rice is a swampy crop with a degree of tolerance to flooding, and rainwater ponding at a certain depth in paddy fields during the main flood period increases rainwater utilization efficiency, save irrigation water, store a portion of flooding water, and relieve the pressure of regional flooding. The rice planting season in humid areas of China coincides with the summer wet season, and the average annual precipitation there is more than 800 mm[6]. Abundant rainfall in humid areas allows for successful rice cultivation in the rainy season with minimal irrigation[7]. Regulating the management of rainwater in existing agricultural infrastructure to leverage the potential contribution of rainwater to irrigation water, is an option for increasing water productivity in irrigated agriculture.

Attempts to reduce nutrient losses in drainage water have resulted in the promotion of controlled drainage (CD), which is

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potentially the best management practice to improve water quality[8]. By holding a high water depth in the field, CD maintains a high depth of water in a field and so reduces drainage rate and drainage volume, it also decreases the quantities and concentrations of nutrients that are wasted in drainage ditches[9,10]. However, field soil moisture condition is not constant throughout a crop season, and the soil may frequently experience alternate wet and dry conditions. An approach known as controlled irrigation and drainage (CID), which combines aspects of AWD and CD, has been developed in China[11]. In CID, a greater water depth than that in AWD is maintained, and more rainwater is captured during rain events[10]. Some studies have founded that compared to AWD, CID reduces irrigation water without significantly affecting grain yield and increases irrigation water productivity[5,11-13]. However, these studies were performed for short time periods and did not allow for the identification of optimal water management practices under various meteorological scenarios. Scientifically based rice irrigation and drainage schemes must be further studied, analyzed, and evaluated.

The growth and development of rice are affected by water management regimes and also by different hydrological years[14,15]. The development of suitable water management practices could inform the strategy design to maintain high rice yields[11,12,16]. However, the development of such practices is time consuming and expensive as it requires data from many years of experimental trials. Irrigation and drainage schemes are extremely complex since many factors need to be considered to achieve long term sustainability in major rice growing areas. Crop growth models can be used to evaluate management options to increase yield and water productivity since they can take account of seasonal variability and weather-related risks and they can be used to spatially and temporally extrapolate experimental results[17]. Many crop growth models have been developed and used to predict the effects of water balance on components of rice, WOFOST[18], EPIC[19,20], CERES[21], and ORYZA[22] are prominent among them. However, the implementation and effectiveness of these models can vary widely according to field characteristics, cropping systems, soil types, and climatic conditions.

Crop systems modeling is a useful tool to investigate the influence of environmental variation and crop management practices on crop growth and to determine resource use efficiencies of farming systems[23,24]. Of these models, the CERES-Rice model has been widely evaluated and applied. Studies have shown that the CERES-Rice model performs satisfactorily in simulating the rice phenology, biomass, grain yield, and actual evapotranspiration (ET_a)[25-27]. Dass et al.[28] used the CERES-Rice model to predict the maturity and yield of these rice varieties grown using intensification methods for different irrigation schemes. Ahmad et al.[29] simulated the effects of plant density and nitrogen application on rice productivity in irrigated semiarid conditions and concluded that the nitrogen application of 200 kg/hm^2 with two seedlings per hill was optimal in terms of nitrogen use and grain yield. Vilayvong et al.[30] used the CERES-Rice model to evaluate the combined effects of transplanting dates, plant density, and nitrogen fertilizer application on under irrigated and rainfed rice in Laos. Nasir et al.[15] assessed the performance of the CERES-Rice model using different sowing dates to simulate mid-century (2040–2069) rice crop for different climatic scenarios and found that the calibration and validation results supported the simulated effects of climate change and possible adaptations to it.

Most models described in the literature used conventional surface irrigation, and there have been few studies that assessed the performance of the CERES-Rice model for rice under water-saving conditions. Further study is therefore needed to assess the performance of the CERES-Rice model under different water-saving conditions to determine if it is suitable for use to develop optimal water management regimes for rice. The objectives of the current study are (1) to evaluate the performance of the CERES-Rice model in simulating the biomass, yield, actual evapotranspiration (ET_a), and water use efficiency (WUE) of rice for different water-saving irrigation schemes; and (2) to determine optimal water management regimes for rice for different water-saving irrigation schemes with different hydrological years.

2 Materials and methods

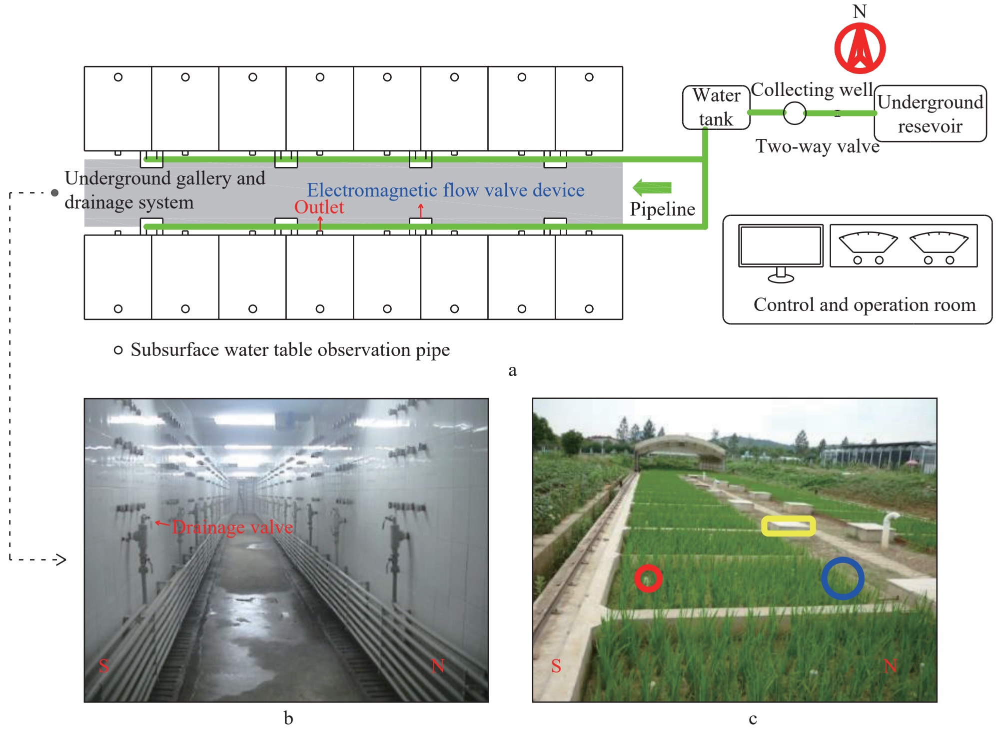
2.1 Sites and experimental conditions

The experiments were conducted from 2018 to 2019 at the Key Laboratory of Efficient Irrigation-Drainage and Agricultural Soil-Water Environment in Southern China, Ministry of Education (Nanjing, latitude 31°57′N, longitude 118°50'E, 144 m above sea level). The experimental site experiences a subtropical humid climate with a mean annual temperature of 15.3°C. The mean annual precipitation at Nanjing City (located 20 km northeast of the experimental site) from 1958 to 2017 is 1047 mm, and the mean annual evaporation is 900 mm[11]. Air temperature, wind speed and direction, relative humidity, total solar radiation, and photosynthesis active radiation were measured every hour at the experimental site using an automated weather station (HL-20, CHN). Precipitation was measured by a tipping bucket rain gauge. All meteorological parameters were stored in a data logger and downloaded weekly to a computer. The annual frost-free period lasts for 220 d. Soil in the area is a typical permeable paddy soil formed on loess deposits with loamy clay. A total of 12 fixed tanks which were made of concrete and steel plate were prepared (length×width×depth = 2.5 m×2 m×2 m). An automatic irrigation system is used in this experiment, which controlled by an electromagnetic valve (Figure 1). The soil (0-30 cm) in the tanks with pH 6.97, consisted of 2.20% soil organic matter, 0.92 g/kg total nitrogen, 27.73 mg/kg available nitrogen, 0.31 g/kg total phosphorus (TP), and 12.2 mg/kg available phosphorus. The physical properties of the soil are listed in Table 1.

2.2 Treatments and experimental design

Four treatments, AWD, CD, CID1 and CID2, were designed for the experiment (Table 2). Treatments were set up in the paddy tanks with closed bottoms; each treatment had three replicates. The tanks were irrigated after transplanting and flooded with a water depth of 30mm above the soil surface for the first two weeks of the experiment for the seedlings to recover and to become established. After two weeks, the water level was allowed to vary., In AWD, CID1 and CID2, the water level was between about −200 mm and 30 mm (with respect to the soil surface) during the tillering stage and the heading and flowering stage and between −300 mm and 30 mm during other stages in normal times. In CD, the water level was allowed to vary between about 10 mm and 30 mm above the soil surface during all four stages. After rainfall, the water level was allowed to reach 30 mm above the soil surface during the tillering stage and 50 mm during other stages in AWD; 60 mm during the tillering stage and 100 mm during other stages in CD and CID1; and 100 mm during the tillering stage and 150 mm during other stages in CID2.

The *japonica* rice cultivar Nanjing 9108 was planted in the seabed on 20 May 2018 and 25 May 2019. The seedlings were transplanted on 23 June 2018 and 29 June 2019 at a precise hill spacing of 0.2 m×0.14 m, with exactly three seedlings in one hill.



Note: (a) Layout of the study area and experimental management. Water was supplied from an underground reservoir to every fixed tank plot through pipelines. (b) Picture of underground gallery and drainage system. (c) Picture of fixed tank plot. Inside the yellow box is the electromagnetic flow valve device. Inside the red box is the subsurface water table observation pipe. Inside the blue box is the outlet.

Figure 1 Experimental site layout

Table 1 Physical properties of the experimental plot used in model evaluation and application

Depth/cm	Field water capacity/%	Saturated water content/%	Total nitrogen/%	Soil organic matter/%	Bulk density/g·cm^{-3}	Grain size distribution of soil		
						Sand	Silt	Clay
0-20	29.43	36.23	0.09	2.2	1.36	40.12	38.21	21.67
20-40	28.23	34.50	0.09	1.8	1.40	39.12	39.16	21.72
40-60	27.01	33.42	0.07	1.6	1.43	39.04	39.95	21.01
60-150	26.98	33.25	0.06	0.9	1.48	40.25	38.12	21.63

Table 2 Physical properties of the experimental plot used in model evaluation and application

Treatments	Tillering stage/mm	Jointing-booting/mm	Panicle initiation/mm	Milky stage/mm
AWD	–200~30~30	–300~30~50	–200~30~50	–300~30~50
CD	10~30~60	10~30~100	10~30~100	10~30~100
CID1	–200~30~60	–300~30~100	–200~30~100	–300~30~100
CID2	–200~30~100	–300~30~150	–200~3~150	–300~30~150

Note: $-I$~J~K mm indicates that water depth was maintained between $-I$ mm and J mm during the stage of rice paddy growth in normal times; and the maximum water height for the treatment after rainfall is K mm.

The experimental plots were dry ploughed and harrowed a week before transplanting. To ensure seedlings were well established, the soil was soaked one day before the experiment and then flooded for a week with a water depth of 20-30 mm above the soil surface. A total of 900 kg/hm^2 of compound fertilizer (N:P_2O_5:K_2O=15:15:15) was basally applied on 23 June 2018 and 28 June 2019. Urea (46.4% N) was used as the tillering fertilizer, and 100 kg/hm^2 was applied on 5 July 2018 and 6 July 2019. Urea was also the panicle fertilizer, and 50 kg/hm^2 was applied on 3 August 2018 and 2 August 2019. Pesticides were applied occasionally, and the weed control was manual.

2.3 Sample collection and measurement

A perforated PVC pipe (60 mm in diameter) was installed vertically to a depth of 1800 mm in the center of each plot to enable observation of the field water depth. The field water depth was observed at 9:00 am using a ruler. When the predetermined minimum level was reached, plot was irrigated until the water level reached the predetermined maximum level. Similarly, when the water level exceeded the maximum because of rainfall, the drainage volume was subsequently calculated by counting the number of opened solenoid valves and then storing the count in a data logger. Precipitation, maximum temperature, minimum temperature, relative humidity, wind speed, solar radiation, and sunshine duration were observed by meteorological stations in the experimental site. Daily maximum and minimum temperatures and rainfall during the two rice growing seasons in 2018 and 2019 are shown in Figure 2.

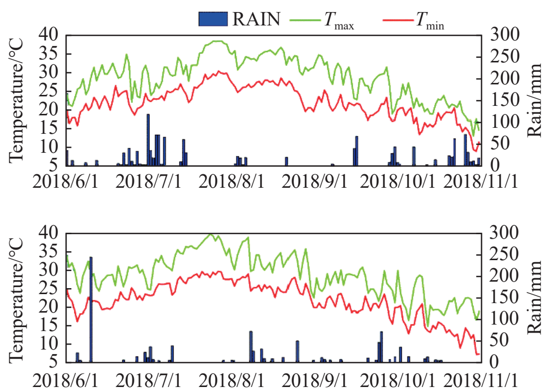


Figure 2 Daily rainfall (Rain), Maximum temperature (T_{max}) and minimum temperature (T_{min}) in 2018 and 2019

The leaf area index (LAI) of rice was measured at 10:00 am by canopy analyzer (SunScan, UK) on sunny days. To determine the above-ground biomass, three hills were sampled randomly from each plot at the beginning of each stage. Above-ground biomass from the three selected plants was measured after oven drying at 75°C for 48 h. Height and tiller numbers were measured from six selected hills. To determine the yield, all ears of the plots were harvested, and the number of harvested plants was counted. Irrigation water use efficiency (IWUE) was the ratio of yield to cumulative irrigation water volume. WUE was the ratio of yield to ET_a. The RWUE was the ratio of the difference between rainfall and drainage volume to rainfall.

2.4 Description, calibration and validation of the CERES-Rice model

The CERES-Rice model (v4.6), a component of the DSSAT software application program, was calibrated and validated in this study. It was embedded in the DSSAT-CSM (cropping system model) platform and was able to call for common modules of weather, soil, and soil-plant atmosphere and management to simulate crop growth, yield, and carbon and water balances[23]. The model requires daily precipitation, daily maximum and minimum air temperatures, and daily solar radiation data as input. It also requires input data on soil characteristics (to calculate evapotranspiration and components of water balance) and management practices, including cultivar, planting date, plant density, and nitrogen fertilization[30].

In this study, the DSSAT-GLUE package[31], which is based on the generalized likelihood uncertainty estimation (GLUE) method[32,33], was used to calibrate the genetic parameters of the rice variety Nanjing 9108. The genetic parameters were calibrated using observations of water use, above-ground biomass at maturity, leaf area index (LAI), and grain yield from the four treatments in 2018. Once calibrated, the model was further validated for the yield, shoot biomass, water use, and water use efficiency of the rice using the data set from the four treatments in 2019. Crop coefficients were categorized into the juvenile phase coefficient P1, photoperiodism coefficient P2R, grain filling duration coefficient P5, critical photoperiod P2O, spikelet number coefficient G1, single grain weight G2, tillering coefficient G3 and temperature tolerance coefficient G4[34]. The model was parameterized by adjusting the soil and genetic file factors that best matched observed and simulated data. Validation was performed to check the accuracy and precision of the model simulations with second-year field experiments having a series of planting dates, which faced a long temperature range and an independent set of data. The validation results showed that the model performance was reliable in simulating rice growth for the different meteorological scenarios. The adjusted genetic parameters used for model validation are listed in Table 3. The performance indicators used to assess prediction accuracy were: absolute relative error (ARE), coefficient of determination (R^2), normalized root mean square error (NRMSE), index of agreement (d), coefficient of residual mass (CRM), mean absolute percentage error (MAPE), standard deviation (SD), and coefficient of variation (CV) were used to evaluate the model prediction capacity; their efficacy has been demonstrated in previous studies[35-37].

Table 3 Rice genetic coefficients under different irrigation and drainage schemes

Irrigation and drainage schemes	Genetic coefficients							
	P1	P2R	P5	P2O	G1	G2	G3	G4
AWD	444	104	566	12.3	74.2	0.022	0.86	0.82
CD	468	104	489	12.3	56.8	0.024	0.93	0.90
CID1	439	164	575	12.9	70.8	0.021	0.90	0.81
CID2	426	189	336	12.1	51.0	0.021	0.84	0.84
Mean value	444	140	492	12.4	63.2	0.022	0.88	0.84
SD	17.6	43.1	111	0.35	11.1	0.001	0.04	0.04
CV	3.96%	30.79%	22.56%	2.82%	17.56%	4.55%	4.55%	4.76%
Calibrated value	444	152	531	12.4	61.5	0.022	0.88	0.84

Note: P1 was juvenile phase coefficient. P2R was photoperiodism coefficient. P5 was Grain filling duration coefficient. P2O was critical photoperiod. G1 was spikelet number coefficient. G2 was single grain weight. G3 was tillering coefficient. G4 was temperature tolerance coefficient.

The equations used for ARE and MAPE are:

$$ARE = \frac{|S_i - O_i|}{O_i} \times 100\% \tag{1}$$

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{(S_i - O_i)}{O_i} \right| \tag{2}$$

where, S_i are simulated values and O_i are observed values. ARE is the relative deviation between observed and simulated data; MAPE is a percentage measure of model prediction accuracy. Lower values of ARE or MAPE indicate higher accuracy and precision of the simulation model.

The equation used for R^2 is:

$$R^2 = \frac{\left[\sum_{i=1}^{n} \left(O_i - \bar{O}\right) \times \left(S_i - \bar{S}\right)\right]^2}{\sum_{i=1}^{n} \left(O_i - \bar{O}\right)^2 \times \sum_{i=1}^{n} \left(S_i - \bar{S}\right)^2} \tag{3}$$

where, $\bar{S}$ is simulated mean values and $\bar{O}$ is observed mean values. R^2=1 indicates a perfect agreement between the observed and simulated data.

The equation used for NRMSE is:

$$NRMSE = \sqrt{\sum_{i=1}^{n} \frac{(S_i - O_i)^2}{n}} \times \frac{100}{\bar{O}} \tag{4}$$

Simulation results are considered "excellent" with NMRSE < 10%, "good" with 10% ≤ NMRSE < 20%, "fair" with 20% ≤ NMRSE < 30%, and "poor" with NMRSE ≥ 30%[38].

The equation for d is:

$$d = 1 - \frac{\sum_{i=1}^{n} (S_i - O_i)^2}{\sum_{i=1}^{n} \left(\left|S_i - \bar{O}\right| + \left|O_i - \bar{O}\right|\right)^2} \tag{5}$$

The values of d range from 0 to 1 and are a measure of data dispersion. d = 1 indicates perfect agreement between observed and simulated data. The d value less than 0.50 indicates great diversity and inconsistency between model predictions. The d value close to

0.0 indicates there is no agreement between observed and simulated values.

The equation used for *SD* and *CV* are:

$$SD = \sqrt{\frac{1}{n}\sum_{i}^{n}\left(O_i - \bar{O}\right)^2} \tag{6}$$

$$CV = \frac{\mathrm{SD}}{\bar{O}} \tag{7}$$

where, *SD* indicates the degree of dispersion among individuals in a group and *CV* indicates the degree of variation in observed values.

2.5 Model application

After the CERES-Rice model had been calibrated and validated, it was used to determine the optimal water management regimes for irrigated rice in the study area on the basis of long-term weather datasets. These datasets contained daily minimum and maximum temperatures, daily rainfall, and solar radiation from 1958 to 2017 and were obtained from the China Meteorological Science Data Sharing Service Network (http://data.cma.cn/). The meteorological station (31°91′N, 118°78′E) is about 18 km from the experimental field (32°07′N, 118°84′E). Total rainfall and rainfall frequency during the main rice growth period (June–October) were calculated for 1958–2017 from the dataset. Precipitation for different growth periods was obtained using the Pearson Type Ⅲ method[39, 40]. The rainfall frequencies $p \leq 37.5\%$, $37.5\% < p < 62.5\%$, and $p \geq 62.5\%$ (p = annual probability of precipitation) were used to categorize annual rainfall as wet (22 a), normal (16 a), dry (22 a) years. The water-saving irrigation schemes simulated were the same as those used in the experimental design (Table 2), and each scheme was simulated for 60 a. The CERES-Rice model includes an automatic irrigation management option that applies irrigation when certain soil moisture conditions are met. This option includes an irrigation threshold value that sets the available soil moisture for a certain depth; both can be defined by the user. The planting date and simulation start date was set to May 20, which was consistent with the local planting date. The model crop cultivar, plant population, row spacing, field fertilizer, and planting depth for the different water management treatments for 60 a were the same as those used in the model calibration and validation. To guide the practice of irrigation and drainage of rice in south China, the entropy-weighting technique for order preference by similarity to an ideal solution (TOPSIS) model was used to optimize the four recommended water-saving irrigation schemes in terms of water-saving, labor-saving, and high-yield on the basis of the simulation results of the CERES-Rice model in the past 60 a. Hwang and Yoon[41] proposed the TOPSIS method, which is an effective method for dealing with multicriteria issues. Here, the underlying principle is to choose an alternative in which the farthest distance exists between the alternative and negative ideal solutions while the shortest distance exists between the alternative and positive ideal solutions. In the process of approach establishment, various influencing factors can be regarded as multicriteria in the TOPSIS method[42].

3 Results

3.1 Calibration and evaluation of the CERES-Rice model

Given the time and space variability of the field experiments and the impact of genotype–environment–management interaction, the genetic coefficients may vary under different water management conditions. First, the genetic coefficients were calibrated using observations from the AWD, CD, CID1, and CID2 treatments in 2018. The calibrated genetic coefficients are shown in Table 3. The variation coefficients of P2R, P5, and G1 were all greater than 15% under the different irrigation and drainage treatments, which indicates that their calculated values were largely dependent on the crop growth scenarios, that is, the water management regimes had a great impact on the three genetic coefficients. Therefore, the mean values of P2R, P5 and G1 across all treatments were taken as the initial settings and then adjusted by the trial and error method. The variation of P1, P2O, G2, G3 and G4 were not obvious under different water management conditions, so their calibrated values were their mean values across all treatments (Table 3). Average ARE values between simulated and observed grain yield, shoot biomass, ET_a, and WUE were respectively 1.38%, 4.71%, 2.39% and 7.08% (Table 5). These results confirmed that the CERES-Rice model was successfully calibrated for the study area and therefore the results are reliable.

Table 4 Simulated and observed values of shoot biomass, grain yield, actual evapotranspiration (ET_a), water use efficiency (WUE), irrigation volume, irrigation water use efficiency (IWUE) given by CERES-Rice for validation.

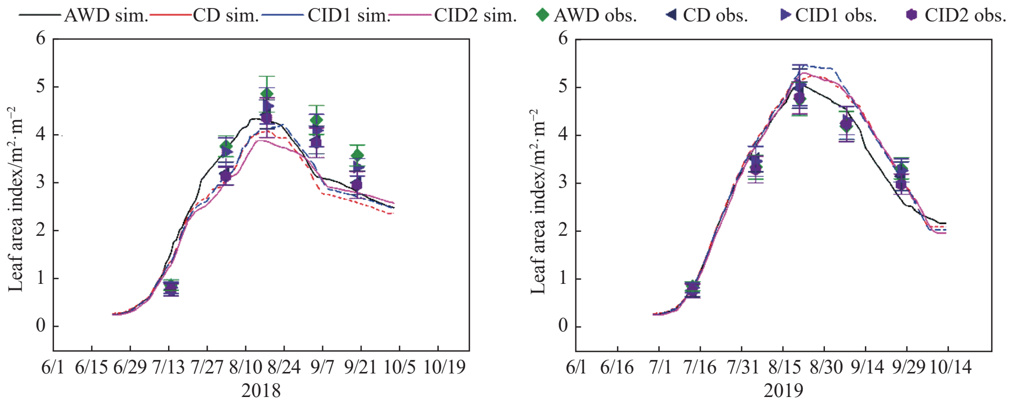
Year		2018 (Calibration)				2019 (Validation)			
Treatment		AWD	CD	CID1	CID2	AWD	CD	CID1	CID2
Grain yield/kg·hm^{-2}	Simulated	9529	8727	9038	8314	9554	8484	9265	8145
	Observed	8915±426	8236±197	8559±401	7946±348	9019±324	8567±255	8883±338	8354±248
	ARE	6.89	5.96	5.60	0.40	5.93	0.97	4.30	2.50
Shoot biomass/kg·hm^{-2}	Simulated	18 637	17 216	17 638	16 432	18 871	18 516	18 934	17 471
	Observed	18 727±905	16 646±841	17 688±863	16 218±694	18 524±962	17 708±891	18 238±904	17 096±796
	ARE	0.48	3.42	0.28	1.32	1.87	4.56	3.82	2.19
ET_a /mm	Simulated	418	456	440	439	399	434	424	406
	Observed	427±10.6	467±12.4	455±11.6	447±9.6	424±8.3	445±12.5	438±11.4	409±9.7
	ARE	2.11	2.36	3.30	1.79	5.90	2.47	3.20	0.73
WUE/kg·m^{-3}	Simulated	2.28	1.91	2.05	1.89	2.39	1.95	2.19	2.01
	Observed	2.09±0.09	1.76±0.05	1.88±0.12	1.78 ±0.07	2.13±0.10	1.93 ±0.08	2.03±0.11	2.04±0.09
	ARE	9.19	8.52	9.20	1.41	12.57	1.54	7.74	1.78
Irrigation volume/mm	Simulated	420	416	358	288	380	384	293	272
	Observed	411±12.3	405±9.5	339±7.9	301±11.3	415±13.4	431±9.1	316±10.1	299±7.5
	ARE	2.19	2.72	5.60	4.32	8.43	10.90	7.28	9.03
IWUE/kg·m^{-3}	Simulated	2.27	2.10	2.51	2.75	2.51	2.21	3.16	2.99
	Observed	2.17±0.13	2.03±0.07	2.52±0.12	2.64±0.14	2.17±0.09	1.99±0.06	2.81±0.15	2.79 ±0.11
	ARE	4.60	3.16	0.01	4.09	15.69	11.15	12.49	7.18

The CERES-Rice model was validated using the experimental data collected in 2019. The average ARE for grain yield, shoot biomass, ET_a and WUE were 3.43%, 3.11%, 3.08% and 5.91% for 2019 (Table 5). The d values of grain yield, shoot biomass, ET_a, WUE and LAI were more than 0.6 for 2019. NRMSE and MAPE were less than 10% for the grain yield, shoot biomass, ET_a, WUE and LAI in 2019 (Table 6), and R^2 values were higher than 0.7. These results showed that the model accurately simulate the grain yield, shoot biomass, and LAI. NRMSE was less than 20% for irrigation volume and IWUE in 2019. These results showed that the model also gave accurate simulations of irrigation volume and IWUE for 2019.

The simulated and observed values for the individual treatments showed good agreement with LAI and above-ground biomass at different growth stages for the different treatments (Figures 3 and 4). LAI increased rapidly at the early stages, reached a maximum value at the jointing and booting or early heading and flowering stage, and then gradually decreased. However, differences were found between simulated values and observation of shoot biomass and LAI during the late stages. This was due to the model not having values of existing water stress that led to inaccurate LAI calculation. It is therefore necessary to improve the performance of the model with respect to water stress.

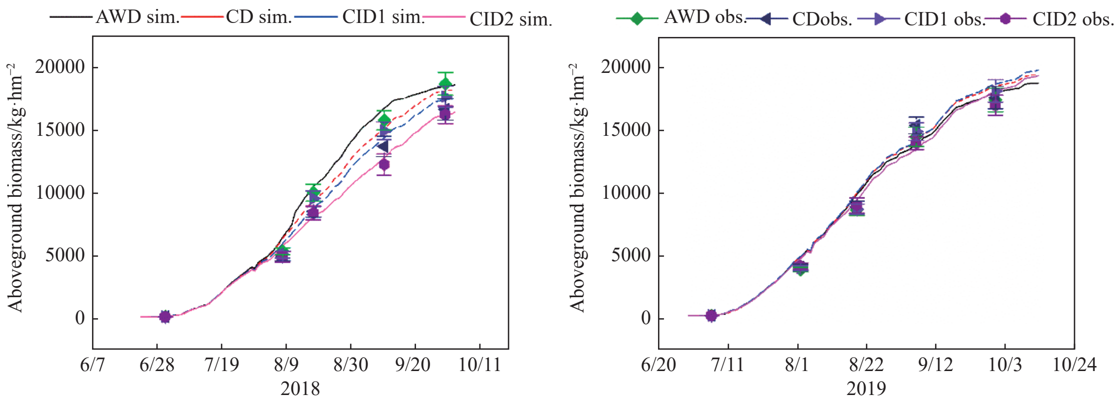
Table 5 Performance indicators for the CERES-Rice model in simulating shoot biomass, grain yield, actual evapotranspiration (ET_a), water use efficiency (WUE), irrigation volume, irrigation water use efficiency (IWUE), leaf area index (LAI) for 2019.

Year	Parameter	R^2	NRMSE	*d*	MAPE
2019	Grain yield/kg·hm^{-2}	0.99	6.83	0.77	4.92
	Shoot biomass/kg·hm^{-2}	0.94	3.77	0.79	3.11
	ET_a/mm	0.84	3.83	0.74	3.07
	WUE/kg·m^{-3}	0.74	9.63	0.63	2.74
	Irrigation volume/mm	0.99	15.56	0.94	7.26
	IWUE/kg·m^{-3}	0.89	15.24	0.86	9.18
	LAI	0.99	9.69	0.98	8.27



Note: sim., simulated value; obs., observed value.

Figure 3 Simulated and observed changes in leaf area index (LAI) for rice in different treatments over two seasons



Note: sim., simulated value; obs., observed value.

Figure 4 Simulated and observed changes in aboveground biomass for Rice in different treatments over two seasons

3.2 Hydrological year groups simulation using long-term weather data

Accumulated rainfall >50.0 mm in 24 h was classed as a storm event and accumulated rainfall ≤50 mm and >25.0 mm in 24 h was classified as a heavy rain event. The volume and frequencies of irrigation and drainage events for the entire rice growth stage for different treatments are listed in Table 7.

The irrigation volume and number of irrigation events of CD were the greatest among the four irrigation and drainage schemes. The irrigation volume of AWD, CID1, and CID2 were respectively reduced by 5.9%, 21.0%, and 30.7% in wet years; 13.2%, 21.8%, and 31.7% in normal years; and 14.9%, 18.1%, and 20.5% in dry years. The number of irrigation events of AWD, CID1, and CID2 were respectively reduced by 17.6%, 29.7%, and 37.4% in wet years; 21.9%, 32.5%, and 40.4% in normal years; and 30.2%, 42.4%, and 43.9% in dry years. The drainage volume and number of drainage events of AWD were the greatest among the four irrigation and drainage schemes. The drainage volume of AWD, CID1, and CID2 were respectively reduced by 2.3%, 17.5%, and 34.1% in the wet years; 2.3%, 22.9%, and 51.4% in normal years; and 7.8%,

Table 6 Numbers of irrigation and drainage and their volume in different hydrological years

Hydrological year groups	Irrigation and drainage schemes	Rainfall/ mm	Number of storm events	Number of heavy rain events	Irrigation volume/mm	Number of irrigation events	Drainage volume/mm	Number of drainage events
Wet year	AWD	700±120	3.6±1.4	8.5±1.6	398±101	7.5±2.7	439±121	13.9±4.4
	CD				423±113	9.1±3.1	389±107	12.5±4.1
	CID1				344±102	6.4±1.1	362±114	10.1±4.6
	CID2				293±105	5.7±1.9	289±97	8.9±3.2
Normal year	AWD	503±86	2.3±1.0	6.1±1.4	405±114	8.9±2.7	218±79	9.6±2.7
	CD				467±129	11.4±3.3	213±76	7.8±2.6
	CID1				365±98	7.7±1.7	168±78	6.0±2.4
	CID2				319±105	6.8±2.5	106±53	5.1±1.9
Dry year	AWD	340±89	1.1±0.9	3.7±1.5	470±123	9.7±3.1	119±52	4.3±2.5
	CD				552±121	13.9±3.7	113±67	3.2±1.9
	CID1				452±104	8.0± 2.0	71±41	2.7±2.2
	CID2				439±113	7.8±2.4	44±29	2.6±1.5

18.1%, and 20.5% in dry years. The numbers of drainage events of AWD, CID1, and CID2 were respectively reduced by 10.1%, 27.3%, and 36.0% in wet years; 18.8%, 37.5%, and 46.9% in normal years; and 25.6%, 37.2%, and 39.5% in dry years. The smaller numbers of irrigation and drainage events were beneficial to farmers in reducing their workload and work intensity. The numbers of drainage events of CID1 and CID2 were <3 in dry years, <7 in normal years, and <11 in wet years. The results indicate that CID1 and CID2 stored rainfall, increased the effectiveness of the paddy wetland, and reduced flood pressure.

ET_a of AWD, CD, CID1 and CID2 was the greatest for dry years among the three rainfall categories (Table 8). Dry years have greater numbers of sunny days and more net solar radiation than normal or wet years. The percolation depth in wet years was greater than that in normal or dry years. Taking CID2 as an example, ET_a for dry and normal years was respectively 6.7% and 13.8% greater than that for wet years, and percolation depth was respectively 6.3% and 10.8% less than that for wet years. ET_a and percolation depth were the greatest for CD and least for AWD. This result may be due to the continuous water ponding which resulted in a high degree of soil water evaporation for CD. Surface water pressure was high for CD, which resulted in high percolation depth. ET_a for AWD, CID1 and CID2 was respectively 8.4%, 4.8% and 4.2% less than that for CD in wet years; 3.3%, 7.0% and 5.1% in normal years; and 8.0%, 6.3% and 5.4% in dry years. Percolation depth for AWD, CID1 and CID2 was respectively 13.2%, 10.7% and 3.9% less than that for CD in wet years; 19.0%, 8.6% and 6.0% in normal years; and 18.0%, 9.8% and 6.3% in dry years.

The yield of AWD was the largest among the four treatments in all hydrological year (Table 8). The yield of CD was the smallest in normal and dry years while the yield of CID2 was the smallest in wet years. Relative to those of AWD, the yields of CD, CID1, and CID2 were respectively reduced by 5.7%, 2.6%, and 8.7% in the wet years; 9.2%, 2.3%, and 8.6% in the normal years; and 9.2%, 3.8%, and 3.9% in the dry years.

Table 7 ET_a and yield of rice in different hydrological years

Hydrological year groups	Irrigation and drainage scheme	ET_a/ mm	Deep percolation/mm	Yield/ kg·hm^{-2}
Wet year	AWD	416±54	243±11	9113±723
	CD	454±67	280±19	8590±815
	CID1	432±65	250±10	8879±518
	CID2	435±59	269±23	8323±751
Normal year	AWD	473±69	222±17	9647±637
	CD	489±73	263±36	8760±568
	CID1	455±53	245±10	9422±624
	CID2	464±57	252±15	8822±665
Dry year	AWD	481±67	215±9	9324±773
	CD	523±76	249±29	8465±642
	CID1	490±59	230±33	8967±617
	CID2	495±64	239±17	8959±601

RWUE for AWD, CD, CID1 and CID2 was the greatest and IWUE and WUE were the least in dry years (Figure 5). Dry years are characterized by greater ET_a and irrigation volume and less drainage volume. RWUE and IWUE for CID2 were the greatest among the four irrigation and drainage schemes, and WUE and IWUE for CID were the least. WUE of AWD was the greatest in wet and dry years, and WUE of CID1 was the greatest in normal years. RWUE of AWD, CD and CID1 was respectively less than that for CID2 by 36.5%, 24.3% and 17.8% in wet years; 28.2%,

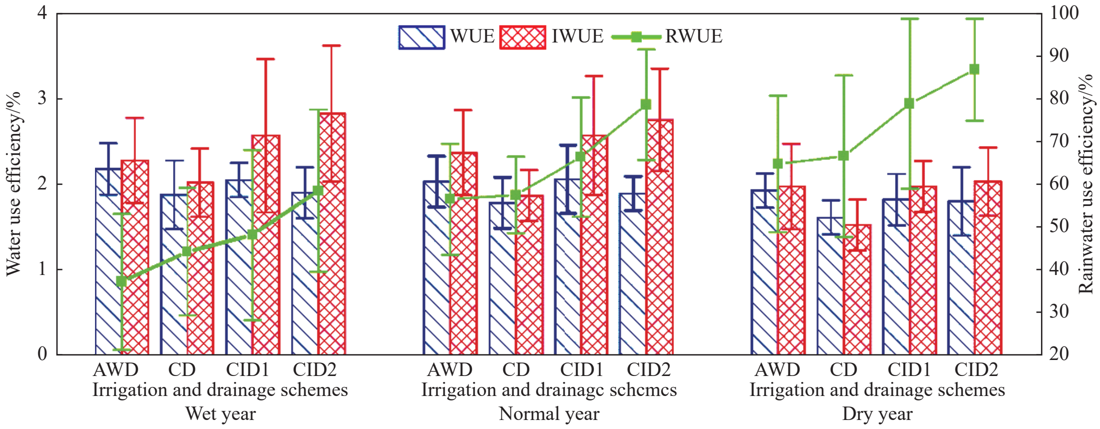


Figure 5 Rainfall utilization efficiency and water productivity of rice under different treatments in different hydrological years

27.0% and 15.6% in normal years; and 25.3%, 23.3% and 9.1% in dry years. IWUE of AWD, CD, and CID1 were respectively less than that for CID2 by 19.4%, 28.5% and 9.1% in wet years; 13.9%, 32.2% and 6.7% in normal years; and 2.8%, 24.9% and 2.8% in dry years.

3.3 Optimization of irrigation and drainage schemes

The TOPSIS model of irrigation and drainage schemes contained three first level indicators and five second level indicators (Table 9). Water-saving, labor-saving, and high yield were selected as the first level indicators. The second level indicators were irrigation volume, RWUE, number of irrigation events, number of drainage events, and yield.

Closeness to the ideal solution indicates the quality of the solution obtained by the entropy-weighted TOPSIS model. The degrees of closeness of AWD, CD, CID1 and CID2 were respectively 0.58, 0.27, 0.68, and 0.47 in wet years; 0.45, 0.12, 0.65, and 0.59 in the normal years; and 0.42, 0.2, 0.72, and 0.85 in the dry years (Figure 6). These results showed that CID1 and AWD were optimal in the wet years and that CID1 and CID2 were optimal in the normal and dry years.

Table 8 Evaluation index level and index assignment

Hydrological year groups	Irrigation and drainage scheme	Water-saving		Labour-saving		High yield
		Irrigation volume/mm	Rainwater use efficiency/%	Number of irrigation events	Number of drainage events	Yield/kg·hm^{-2}
		Negative	Positive	Negative	Negative	Positive
Wet year	AWD	398	37.3	7.5	13.9	9113
	CD	423	44.4	9.1	12.5	8590
	CID1	334	48.3	6.4	10.1	8879
	CID2	293	58.7	5.7	8.9	8323
Normal year	AWD	405	57.7	8.9	9.6	9647
	CD	467	56.7	11.4	7.8	8760
	CID1	365	66.6	7.7	6.0	9422
	CID2	319	78.9	6.8	5.1	8822
Dry year	AWD	470	66.8	9.7	4.3	9324
	CD	552	65.0	13.9	3.2	8465
	CID1	452	79.1	8.0	2.7	8967
	CID2	439	87.1	7.8	2.6	8959

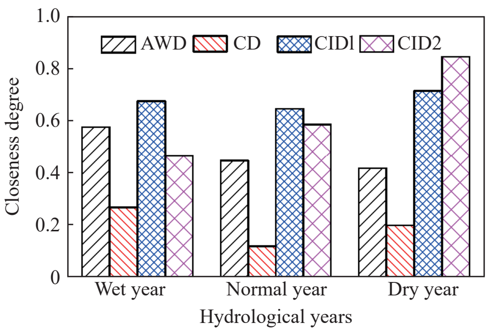


Figure 6 Closeness of entropy-weighted TOPSIS model solutions for different irrigation and drainage schemes in different hydrological years

4 Discussion

The underlying assumption in crop modeling applications is that the model can accurately simulate the processes occurring within the agricultural system. According to Jamieson et al.[38], differences between observed and simulated values falling within 20% are considered acceptable in crop model simulations. Overall, the model in the current work satisfactorily simulated the grain yield, shoot biomass, and LAI (NRMSE and MAPE were both less than 16%, R^2 ranged from 0.74 to 0.99 and d ranged from 0.63 to 0.98) (Table 6). The disparities between observed and simulated values were attributable to the actual crops in farmers' fields being affected by weeds, diseases, pests, and other factors, which were not taken into account by the model[43,44]. Vilayvong et al.[30] confirmed the ability of the calibrated CERES-Rice model to accurately simulate grain yield and biomass of rice with NRMSE<15%. Ahmad et al.[29] obtained the excellent accuracy in simulating LAI and aboveground biomass of rice with NRMSE<5% and R^2>0.9. A previous study found that the CERES-Rice model was highly accurate with adequate water supply but inaccurate with water stress conditions[37,45]. It was found that the simulation was good for different irrigation and drainage schemes, in which rice may frequently be subject to flooding and drought stress, although water stress was not present for the entire rice growing period in the different irrigation and drainage schemes used in this study. A complex model requires a large number of parameters, which vary with environmental conditions, local crop cultivars, and other factors[46]. However, calibrating all unknown parameters may be unnecessary. Only few model parameters influence the model's key processes and most of its output, and the model works well when only these parameters are calibrated accurately before application of the model[22,47,48]. This characteristic may explain why P2R, P5, and G1 should be calibrated again by trial and error. Therefore, it is necessary to identify the importance of various parameters improve the performance of the CERES-Rice model under water stress conditions.

That the accuracy of ET_a and WUE predictions were acceptable was indicated by high values of R^2 and d (R^2>0.74; d>0.63) and low values of NRMSE and MAPE (NRMSE and MAPE were less than 10%) (Table 6). Several studies have reported good predictions of ET_a and WUE using the DSSAT model[21,49,50]. However, we obtained NRMSE values for irrigation volume and IWUE were more than 10%. This result suggests that some components of soil water balance of the CERES-Rice model should be improved to obtain reasonable irrigation and IWUE.

Drainage is important to crop growth. It has been found that for dry land crops, there is no significant increase in yield was found relative to the conventional drainage conditions (P < 0.05)[51]. In contrast, for wetland crops like rice, CD significantly increased yield (p<0.05)[52]. The present study found that CD had the lowest yield in all categories of hydrological years (Table 8). This result may be due to the maximum water level of CD after rainfall having been set too high when compared with the real situation. Moreover, a constant water level throughout the growth stage of rice may be unfavorable to root growth and may affect grain yield[16]. In contrast to CD treatment, AWD can decrease irrigation volume by up to 38% with no yield reductions if implemented correctly[4]. Tan et al.[53] found that AWD reduced irrigation water without a significant effect on grain yield and increased mean WUE by 16.9% compared with CD treatment. The present study found that yield and WUE were the greatest for AWD in all categories of hydrological years (Table 8 and Figure 5). However, the drainage volume was also the greatest for AWD in all categories of hydrological years and resulted in a low RWUE. This was because the water level reached a depth of only around 50 mm in the AWD implementation.

Mdemu et al.[54] and Shao et al.[12] found that IWUE of rice for CID was greater than that for AWD due to the contribution of rainfall. We found that IWUE for CID1 and CID2 was greater than that for CD and AWD because of greater RWUE. Yield for both CID1 and CID2 was less than that for AWD, but the yield for CID1 and CID2 differed greatly. Yield for CID1 was marginally less than that for CID2 (2.5% in wet years, 2.3% in normal years, and 3.8% in dry years). In wet and normal years, CID2 resulted in a greater yield loss (more than 8%) than CID1 (Table 8 and Figure 5). The decrease may be attributed to the adverse influence on the rice root system by the reduced root oxidizing power as a result of the oxygen deficiency under a high ponded water table and continuous flooding in wet and normal years[55]. In terms of economic effects, Lampayan et al.[4] found that water savings can increase farm income by as much as 17% in Vietnam, 32% in the Philippines, and 38% in Bangladesh. AWD had a relatively low frequency of irrigation events, which reduced the labor costs of irrigation. However, we found that irrigation volume, and numbers of irrigation and drainage events for CID1 and CID2 were lower than those of AWD (Table 7). These results illustrate that CID is a better irrigation and drainage scheme than AWD. Moreover, CID1 was optimal in wet and normal years and CID2 was optimal in dry years.

This study showed that the CERES-Rice model could satisfactorily simulate the growth and yield of rice for different irrigation and drainage schemes. The model results provide general guidelines for the selection of cultivars, fertilizer quantities, seedling per hill, and optimum transplanting date for high rice production and highest net income for different irrigation and drainage schemes. Previous studies have found that water-saving technologies reducing nonpoint source pollution, fertilizer loss, and greenhouse gas emissions[10,56]. Optimization of irrigation and drainage schemes also needs to consider the advantages of emission reduction and pollution control. In the warming climate, changes in hydrological and climatic conditions will continue to affect crop water consumption and yield, and the potential application and robustness of various water-saving irrigation schemes need to be further studied.

5 Conclusions

The calibrated CERES-Rice model performed well in simulating rice ET_a, water use, shoot biomass, LAI, and grain yield for different irrigation and drainage schemes. However, if the irrigation and drainage management of paddy field change significantly, then P2R, P5, and G1 should be calibrated accurately. The calibrated CERES-Rice model was also used to determine the most suitable irrigation and drainage scheme for rice using 60 a of historical weather data. WUE of AWD was the greatest for the four schemes in the wet and dry years, and WUE of CID1 was the greatest in normal years. RWUE and IWUE of CID2 were the greatest for the four schemes. Yields of CD, CID1, and CID2 were respectively less than the yield of AWD by 5.7%, 2.6% and 8.7% in wet years; 9.2%, 2.3% and 8.6% in normal years; and 9.2%, 3.8% and 3.9% in dry years. Taking water-saving, labor-saving, and high yield as optimization parameters, irrigation volume, rainwater utilization rate, numbers of irrigation events, numbers of drainage events and yield were selected to optimize the irrigation and drainage schemes. The result showed that CID1 and AWD were optimal in the wet years and that CID1 and CID2 were optimal in the normal and dry years.

Acknowledgements

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