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Dynamic within-season irrigation scheduling for maize production in Northwest China: A Method Based on Weather Data Fusion and yield prediction by DSSAT

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ABSTRACT

Current water consumptions are unsustainable in many regions, which requiring more efficient agricultural water management strategies. This study incorporated the DSSAT-CERES-Maize model with a new algorithm for dynamic within-season irrigation scheduling for maize (*Zea mays L.*) based on trends in daily forecasted yields. Field experiments were undertaken at four arid and semiarid sites in Northwest China, including Changwu (2010 and 2011, rainfed), Yangling (2014 and 2015, irrigated), Jingyang (2015, irrigated), and Shiyanghe (2015, irrigated). Historical 50-year (1968–2017) weather data were available for each site. In daily yield forecasts, weather data before forecast dates were observed from local weather stations, while the unknown data between forecast and harvest dates were supplemented by local 50-year continuous weather series in the same periods. Then 50 maize yields could be obtained on each forecast day, and the median values were calculated as the prediction on that day. As the growing season advanced, historical weather data were gradually replaced by actual weather data. Further, the dynamics of daily forecasted yields were used to schedule irrigation based on a new algorithm. The new algorithm schedule irrigations by considering the feedbacks of maize grain yield to interactions of actual weather, environment, and management. The results showed that forecasted maize yield had considerable uncertainty before tasseling but rapidly converged to the actual yield about one month before harvest. The mean absolute relative errors (MAREs) of daily forecasted yields were 11.7% and 7.3% at Changwu in 2010 and 2011, respectively. Simulated irrigation use efficiency (IUE) for almost all sites and years were improved. The new irrigation scheduling algorithm will help to improve irrigation scheduling in arid and semiarid areas where precipitation is the main limited factor to maize yield.

1. Introduction

Structural change and growth consumption in livestock sectors and industry has increased the demand for maize, making it one of the most important crops in China (Qin et al., 2016). In 2017, China had 42.3 million ha sown to maize, yielding 259.1 million ton of grain (National Statistical Bureau of China, 2017), mainly under drought-prone weather conditions in northern China. Agriculture is the largest water user worldwide and is severely affected by water shortages. Irrigation is often used to ensure food production (Kang et al., 2017). The FAO (2015) reported that irrigated farmland accounts for only 18% of the total fields worldwide, but produces nearly 40% of all food for people. In recent years, the increase in greenhouse gas emissions has resulted in more drought events (Hsiao et al., 2007), necessitating more efficient field management practices for water managers and farmers alike.

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Traditional irrigation management involves the transport of water in the soil–plant–atmosphere continuum (SPAC), with irrigation schedules were usually based on statistical measurements of soil moisture, plant water content, ET, rainfall, and crop growth status (e.g., grain yield and aboveground biomass) (Fang et al., 2017; Hrkac et al., 1986; Liu et al., 2002; Thorp et al., 2017). With improvements in sensors, data transmission and storage, the above indicators can be transmitted in real-time to establish irrigation scheduling systems (Thysen and Detlefsen, 2006; Yang et al., 2017). However, the purpose of irrigation is to increase grain production, not maintain soil moisture or plant water content, although irrigation strategies scheduled by field experiments and statistics do meet the crop water requirements for each growth stage. Due to limited year types and treatments of field experiments, traditional irrigation methods are unable to quantify the influence of irrigation date and amount on crop growth and development for variable weather conditions, crop genotypes, soil types, and agronomic practices across different years and regions.

In recent years, field experiments combined with crop model simulations have been used to determine irrigation schedules, since crop models can dynamically quantify crop growth responses to farmland environments. Rogers and Elliott (1989) used a cost/loss (C/L) risk analysis to determine the level of irrigation for grain crops in Oklahoma and reported that the application of C/L could reduce irrigation water compared with purely biophysical-based irrigation scheduling methods. Saseendran et al. (2008) applied the CERES-Maize model to optimize irrigation for maize in northeastern Colorado based on water requirements at different growth stages. Kisekka et al. (2016) generated optimum deficit irrigation strategies for maize production in Kansas based on the CERES-Maize model and long-term weather records. They indicated that this model could be used as a decision support tool for assessing irrigation strategies that optimize the use of limited water and maximize the net returns for maize production. However, most studies on optimizing irrigation strategies using crop models have focused on irrigation scheduling options based on limited experimental data and simulations with long-term weather data (Anothai et al., 2013; He et al., 2013; Lopez et al., 2017a). Few studies have reported using crop simulation models for irrigation scheduling based on real-time weather conditions, or how seasonal yields are affected by irrigation. When crop models are used in plant growth simulations, weather data are needed for the entire growing season. Due to the low accuracy of long-term weather forecasts, crop modeling studies have mainly focused on assessing crop growth and development after the growing season had ended (Araya et al., 2015; He et al., 2011). Effective within-season climate prediction could assist farmers in managing farmland and minimizing risk (Prakash et al., 2019; Semenov and Doblas-Reyes, 2007), but more studies using medium- or long-term meteorological forecasts are needed to improve the precision of crop model predictions (Ferrise et al., 2015). Some researchers have used historical weather data combined with real-time weather data to generate multiple complete climatic data series covering the entire growing season, to forecast crop growth and yield (Bannayan and Hoogenboom, 2008; Lawless and Semenov, 2005). In this way, weather series could be generated on every day in the growing season by incorporating local historical and daily new measured weather data. Hence, maize growth status and grain yield related to actual weather conditions could be forecast on every day before harvest (Chen et al., 2017).

In the process of daily forecasting maize yields, soil, field management and cultivars are usually kept the same. Thus, any differences between forecasted yields on different dates were caused by the changed days with actual weather data in the generated weather series. In arid and semiarid areas of China, maize yield is mainly determined by accumulative rainfall of the whole growing season (Jiang and Li, 2015). A decline trend in daily forecasted yield might indicate that the accumulative rainfall in the comparison period resulted in more serious water stress. The mainly because if soil water content increased or keep the same, yield predictions should not reduce. Irrigation could then be used to mitigate the risk associated with weather variability in maize production. Based on daily forecasted yields and their general trends, water resource managers can offer suggestions for irrigation, according to the availability of water, in the search for a cost-effective water management strategy.

In this study, a new irrigation scheduling algorithm was developed based on the DSSAT-CERES-Maize model and dynamic weather data fusion. The main objectives were to: (1) assess the precision of within-season forecasts of maize grain yield based on the CERES-Maize model and dynamic weather data fusion, and (2) evaluate the new dynamic irrigation scheduling algorithm for maize production in arid and semiarid areas in China. This work is expected to provide a new tool for dynamic within-season irrigation scheduling for maize production in Northwest China.

2. Materials and methods

2.1. Experimental sites

Four experimental sites in Northwest China were selected for this study, including Yangling (34°17′N, 108°04′E, 506 m; YL), Jingyang (34°32′N, 108°50′E, 411 m; JY), Changwu (35°14′N, 107°52′E, 1220 m; CW) in Shaanxi Province, and Shiyanghe (37°52′N, 102°50′E, 1581 m; SYH) in Gansu Province (Fig. 1). Mean annual rainfall ranged from 550–650 mm for the three sites in Shannxi Province and only 162 mm for Shiyanghe in Gansu Province. The annual rainfall at these sites was temporally uneven as most rainfall occurred in summer.

Summer maize was planted in Yangling (2014 and 2015, irrigated) and Jingyang (2015, irrigated), while spring maize was planted in Changwu (2010 and 2011, rainfed) and Shiyanghe (2015, irrigated) (Table 1). Changwu, located in the southern part of the Loess Plateau of China, was the only rainfed experimental site due to the lack of irrigation facility. Irrigation in the three irrigated experiments followed the actual management practices of local farmers in border flooding. All fertilizers were applied once at planting as basal fertilizer.

2.2. Brief description of the DSSAT-CERES-Maize model

DSSAT is one of the most popular process-oriented cropping system models (CSM), which can simulate daily crop growth and development, including phenological states, biomass production and grain yield. Before running the model, users should input weather factors, soil profile, cultivar-specific parameters, and field management data (Hoogenboom et al., 2017; Jones et al., 2003). DSSAT can track carbon, nitrogen, water, and energy exchange processes. In DSSAT, crop growth is simulated using specific CSMs. CERES-Maize is one of the CERES (crop environment resource syntheses system) series models, as are CERES-Sorghum, CERES-Wheat, and CERES-Barley (Lopez et al., 2017b; Otter-Nacke et al., 1991; Ritchie and Otter, 1985; White et al., 2015). CERES-Maize consists of nonlinear, dynamic mathematical functions that describe maize growth and yield formation as well as changes in soil water and nutrient contents at a field-scale. The CERES-Maize model simulates maize growth by considering field practices and is driven by daily weather conditions. It can simulate the growth and development of roots, shoots, leaves and stems, biomass accumulation and partitioning between roots, shoots, leaf, stems, and fruits. Readers can refer to Jones et al. (1986) for a complete description of CERES-Maize.

Four groups of data are generally needed for DSSAT simulation: weather, crop, soil, and management. Daily weather data include maximum air temperature (*Tmax*, °C), minimum air temperature (*Tmin*, °C), rainfall (*Rain*, mm), and solar radiation (*SRAD*, MJ m^{-2}). Crop parameters and physiological performance are represented by genetic coefficients. Soil inputs are given as parameters, including physical, chemical, and morphological properties of each soil layer. Crop management information includes crop cultivar, planting date, depth and

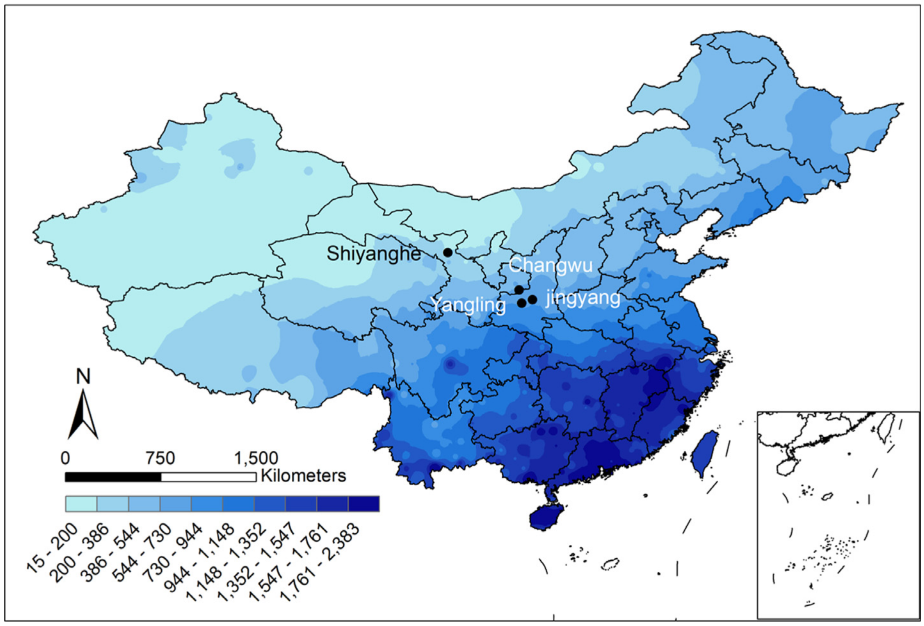

Fig. 1. Distribution of mean annual rainfall in China. Black points indicate experimental sites. The Shiyanghe site, with actual mean annual rainfall of 162 mm, was located at the junction between the first (15–200 mm) and second (200–386 mm) rainfall levels due to the classification resolution in the ArcGIS software.

density, row space, irrigation, fertilizer, and application of organic amendments. To promote the use of a minimum data set, a simple water balance algorithm named "tipping-bucket" approach is embedded in the CERES-Maize model to calculate yield reduction caused by water stress. In this model, maize development rates are calculated based on air temperature and photoperiod. Biomass generated from photosynthesis in green organs is affected by daily minimum temperature. Due to the simplification of water transfer cycles, large simulated errors occur in DSSAT models with high water stress.

In this study, weather data were obtained from the China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). Since solar radiation data were not available for the four sites, daily cumulative solar radiation was calculated by daylight and sunshine hours using Angstrom's formula (Angstrom, 1924). Soil parameters and management practices were obtained directly from documented on-farm observations. Crop cultivar parameters were estimated using the DSSAT-GLUE package (He et al., 2009; Jones et al., 2011) based on field observations of important phenology dates, biomass, and yield of maize.

2.3. Dynamic within-season irrigation scheduling

DSSAT-CERES-Maize is a processing model that simulates plant growth by taking into consideration the environment, agricultural management practices and crop genotype. To run the CERES-Maize model, weather data series covering the whole growing season is needed. In the process of daily yield prediction, actual weather data were measured every day at the local weather station. The unknown weather data between forecasted and harvest dates were represented by the same-date historical weather records (1968–2017) for the local site. An integrated weather data series was then generated and updated by incorporating the newly measured weather data. In this way, seasonal maize yield which considering actual weather data were predicted daily during the growing season. Trends in daily forecasted yields were used to guide irrigation, and irrigation strategies would be added to the CERES-Maize model to simulate maize growth. By incorporating the real-time weather data into the generated weather series and assessing their impact on seasonal maize grain yields dynamically, we could schedule irrigation by considering the weather, soil, and agronomic

Table 1
Main soil, weather, and management information of the four experimental sites. YL, CW, JY, SYH are the sites at Yangling, Changwu, Jingyang, and Shiyanghe, respectively.

Soil, weather and management	Sites					
	YL		CW		JY	SYH
Soil type	Silty loam		Clay loam		Silty clay loam	Sandy loam
Bulk density (g cm^{-3})	1.31		1.32		1.41	1.47
Field capacity (cm^{-3} cm^{-3})	0.26		0.22		0.24	0.35
Mean annual temperature (°C)	12.3		9.2		13.1	8.2
Mean annual rainfall (mm)	637		560		547	162
Cultivar	*Zhengdan-958*		*Xianyu-335*		*Wuke-2*	*TRFA*
Planting density (plants ha^{-1})	55 000		85 000		75 500	97 500
Year	2014	2015	2010	2011	2015	2015
Planting date	12-Jun	12-Jun	24-Apr	24-Apr	10-Jun	15-Apr
Harvest date	27-Sep	24-Sep	13-Sep	13-Sep	29-Sep	20-Sep
Irrigation amount (mm)	160		–		270	442
N	210		138		180	219
Fertilizers (kg ha^{-1})						
P	96		38		80	–
K	77		–		–	–

practices simultaneously.

2.3.1. *Within-season maize yield forecasts based on weather data fusion*

Weather data for the whole growing season are needed to run the models to forecast maize yield dynamically. By incorporating newly measured daily weather data and historical weather data, we can forecast maize yield in Northwest China with high accuracy on a daily basis within the growing season (Chen et al., 2017). The weather data for each growing season were divided into two parts (actual and predicted). Daily actual weather data were collated from local weather stations, while predicted weather data for the remaining days were replaced by 50-year historical weather data (1968–2017). For example, the summer maize growing season at Yangling was about 110 days. At sowing, the 50-year historical weather series were taken as 50 possible scenarios for the target growing season such that 50 possible maize yields were available from the CERES-Maize model simulations. On the second day after sowing, actual weather data were available from the local weather station for the first day, while data for the remaining 109 days were unknown and then replaced with historical data for the same dates. Consequently, another 50 forecasted grain yields were calculated on the second day of the growing season. As the maize growing season advanced, newly measured daily weather data were gradually added into the weather series. With the fusion of real-time weather data and 50-year historical weather data, multiple complete climatic data series were created and used to run the CERES-Maize model to forecast maize growth and yield on each day.

2.3.2. *Sensitivity of maize yield to weather variables*

To determine which weather variables affected maize yield the most in the study areas, we analyzed the sensitivity of maize yield to four different weather variables (*Tmax, Tmin, Rain*, and *SRAD*) in the CERES-Maize model simulation. Experimental files were set up in the model according to actual field management practices at each site. Daily mean values for the four weather factors were calculated from 1968 to 2017 before generating three different types of weather data series. For each type, the actual values for one weather factor were retained each year, while 50-year means values were used for the daily values of the other three weather factors. It should be noted that if the mean valued of *Tmin* > *Tmax*, then the model might not run. To avoid this, *Tmin* and *Tmax* were treated as one weather factor and replaced simultaneously. Three types of maize grain yield across 50 years were determined by running the CERES-Maize model with the three types of weather series generated above. The distribution of simulated maize yields under different climatic scenarios was then analyzed.

2.3.3. *Algorithm for dynamic with-season irrigation scheduling*

Based on the dynamic maize yield forecast method and sensitivity analysis of maize yield to different weather variables in the study areas, a new automatic irrigation scheduling algorithm and software were established (Fig. 2). The main steps of the algorithm are summarized below.

Step 1. *Trend analysis of daily forecasted yields*. Based on the fusion of daily measured weather data and 50-year historical weather data from local sites, 50 different possible yields could be forecasted each day in a given growing season. The daily forecasted yield was calculated as the median of the 50 simulated yields to avoid the influence of extreme weather conditions. The trend of forecasted maize yields was analyzed using linear regression, and the slope of the regression line (*Si*) was calculated on the *i-th* day of the growing season. The number of accumulative days (*ad*) of forecasted maize yields with continuous negative slopes of the regression line was counted to indicate the influence of forecasted maize yields by weather conditions.

Step 2. *Dynamic within-season irrigation scheduling*. In the process of daily yield forecasting in the CERES-Maize model, management, soil and crop cultivars settings remained the same, except for the weather files due to newly measured daily weather data. Any differences in forecasted yields on different dates were probably caused by variations in weather data (Fig. 3). From Section 2.3.2, rainfall was identified as the most influential and limiting weather factor for maize yield in the study areas. Therefore, a continuous decreasing trend in predicted yields for a given number of days usually meant that actual rainfall in the target period was less than normal historical years. In fact, the lesser precipitation resulted in more serious water stress because the forecasted yield should not decline if the precipitation meets maize water requirements. To avoid a further decline in forecasted yield, irrigation should be applied. In this study, we defined the irrigation threshold IT(*DD, ID*) as a function of *DD* and *ID*, where *DD* is the threshold number of accumulative decreasing days of forecasted yields and *ID* (mm) is the irrigation depth. If the number of accumulative decreasing days of forecasted yields (*ad*) exceeded the threshold *DD*, irrigation at depth *ID* would be added to the irrigation module in the XFile (model system file with experimental information) in DSSAT on the same date. Then, the accumulative decreasing days *ad* was reset to 0. The IT(*DD, ID*) function can be set according to locally available agricultural water resources and yield expectations.

Step 3. *Automatic Irrigation Scheduling Software (V1.0)*. Based on the algorithm above, a program for automatic irrigation scheduling was developed using R language (*V3.4*) (R Core Team, 2013). First, users set up and run the CERES-Maize model in DSSAT based on actual field experiments. Next, weather data files for historical and target years (a separate document for each year) are saved in a specified directory. Daily newly measured weather data are gradually fused into the weather data files of the target year. Third, the R codes are run to enter the graphic user interface (GUI) of the program due to the weakness in GUI design in R Language (Fig. 2b). In the GUI, the left column is information that users needed to input, including: *Site name* (first four letters of the DSSAT-XFile name), *Target year, Starting year* and *Ending year* of historical weather data, *Starting date* and *Ending Date* of irrigation scheduling period (days after planting, or dap), irrigation depth per event (*ID*, mm), and accumulative decreasing days of forecasted yields (*DD*, d). Finally, click the *Run* button to start automatic irrigation scheduling on each day during the growing season; daily forecasted yields and irrigation events are displayed in the right window of the GUI.

2.3.4. *Evaluation of the automatic irrigation scheduling program*

To test the influence of irrigation date and depth on maize grain yield in the new program, we used different IT(*DD, ID*) scenarios to simulated maize growth and schedule irrigation at Changwu (rainfed) in 2011. Maize yield was forecast on each day during the growing season under four different IT(*DD, ID*) scenarios, i.e., IT(10, 40), IT(10, 80), IT(15, 40), and IT(15, 80). To evaluate the efficiency of the irrigations scheduled by the new algorithm, we compared simulated final grain yields, irrigation times, total irrigation depths, and irrigation use efficiencies (IUE) of the different irrigation schedules based on (1) local farmer experience, (2) the automatic irrigation option in DSSAT and (3) the new within-season irrigation scheduling program at the three irrigated experimental sites. The comparison objects included simulated final grain yields, irrigation times, total irrigation depth, and IUE.

In the automatic irrigation option in DSSAT, soil volumetric water content was used as an indicator for irrigation scheduling. Users should define three variables before using this module, management depth (cm), threshold, and end point of irrigation (percent of maximum available water holding capacity, or AWAC). Here, we took the default values as an example, where management depth was 30 cm, and the threshold of soil volumetric water content and end point for irrigation were 50% and 100%, respectively. In the new irrigation scheduling program, the parameter of *DD* was set at ten days and *ID* had two levels: local application and half of local application. It should be noted that the annual average rainfall in Shiyanghe (about 162 mm) was too low

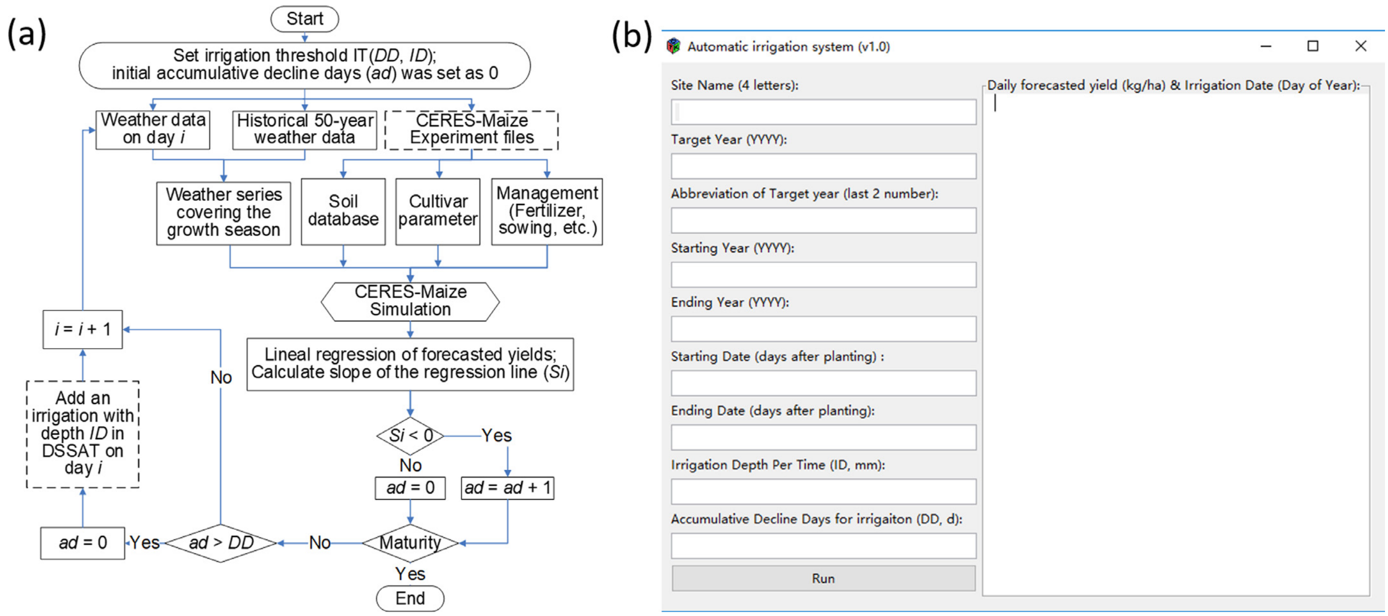

Fig. 2. Flowchart (a) and interface (b) of the dynamic within-season irrigation scheduling program based on weather data fusion and the DSSAT-CERES-Maize model. An irrigation event was triggered by a threshold of IT(*DD, ID*), a function of the accumulative declining days (*DD*) of daily forecasted yields and irrigation depth (*ID*) per event within a given growing season. Slopes of the linear regression were used to judge the reducing trend of daily forecasted yields and the number of accumulative declining days of forecasted yields.

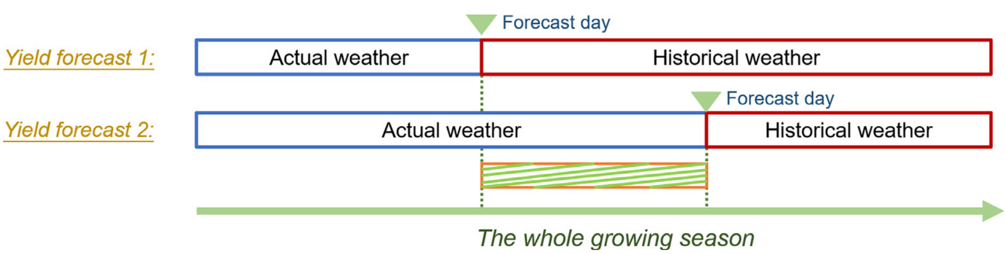

Fig. 3. Illustration of forecasted yields with different proportions of actual and historical weather data. The shaded part illustrates the portion of historical weather data replaced by actual weather data, resulting in different forecasted yields on different dates. Actual weather data were measured each day within the growing season, by local weather stations, while the weather data of following days in the growing season were replaced by local 50-year historical weather data (1968–2017).

to satisfy maize water requirements. All of the simulated rainfed maize yields were < 2000 kg ha^{-1} in the past 50 years, which was much lower than actual local maize production. Thus, the new irrigation scheduling program failed to find the decreasing trend of forecasted maize yield needed for the irrigation decision. To avoid such a failure of the new irrigation scheduling program under extremely dry conditions, a pre-determined irrigation at the maize tasseling stage was set in the model according to local experience. With this basic irrigation, the variation in daily simulated maize yield increased in different weather scenarios. In this study, irrigation at a depth of 110 mm was set on the *96th* day after planting according to local farmers.

2.4. Statistical analyses

The absolute relative error (ARE, Eq. 1) was used to evaluate the accuracy of model calibration and yield forecasting. Mean absolute relative error (MARE, Eq. 2) was used to analysis the general yield simulation accuracy of the whole growing season. Irrigation use efficiency (IUE, kg ha^{-1} mm^{-1}, Eq. 3) was used to evaluate the irrigation use results of different scheduling methods and irrigation threshold functions of IT(*DD, ID*) on maize grain yield (DeJonge et al, 2011).

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

$$\mathrm{MARE} = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \frac{|O_i - S_i|}{O_i} \times 100\% \tag{2}$$

$$\mathrm{IUE} = \frac{Y}{TI} \tag{3}$$

where O_i and S_i are observed and simulated values of given parameters, respectively; n is total forecast times in the target growing season; *Y* is maize grain yield (kg ha^{-1}), and *TI* is total irrigation depth (mm).

3. Results

3.1. Calibration and verification of the CERES-Maize model

To assess the prediction accuracy of the CERES-Maize model for maize grain yield, biomass, and key phenology dates (tasseling and maturity), we calculated the AREs between simulated and observed values of these variables (Table 2). We mainly focused on the ability of the CERES-Maize model to simulate maize yield and phenology dates, since they were used in our new irrigation scheduling program, and paid less attention to simulated soil water dynamics and other processes. In general, the CERES-Maize model simulated the four variables well, with especially good results for tasseling date and yield. The AREs were < 13.3% for all treatments over the four years and four sites. The simulation error in tasseling date was less than two days, but the error of maturity date was relatively high, which resulted from the difficulty

Table 2

Comparisons between observed and simulated values in the CERES-Maize model of two phenology dates (tasseling and maturity), grain yield, and biomass of maize at four experimental sites.

Site	Year	Rainfall (mm)	Irrigation scheduling Method	Depth per event (mm)	Determination factor	Irrigation times	Total amount (mm)	Simulated yield (kg ha^{-1})	IUE [a] (kg ha^{-1} mm^{-1})
JY	2015	218	Actual	90	Local experience	3	270	11326	41.9
			DSSAT auto-option	–	Soil moisture	6	280	12077	43.1
			New program [b]	90	Forecasted	3	270	11274	41.8
				45	yields	4	180	9929	55.2
YL	2014	381	Actual	80	Local experience	2	160	6150	38.4
			DSSAT auto-option	–	Soil moisture	2	119	6153	51.7
			New program	80	Forecasted	2	160	6148	38.4
				40	yields	3	120	6149	51.2
	2015	271	Actual	80	Local experience	2	160	7069	44.2
			DSSAT auto- option	–	Soil moisture	3	130	7018	54.0
			New program	80	Forecasted	1	80	7159	89.5
				40	yields	1	40	6245	156.1
SYH	2015	151	Actual	123 + 103 + 113 + 41 + 62	Local experience	5	442	8747	19.8
			DSSAT auto- option	–	Soil moisture	9	387	8963	23.2
			New program	90 + (110) [c]	Forecasted	2 + 1	290	8420	29.0
				45 + (110)	yields	3 + 1	245	7845	32.0

[a] YL, CW, JY, and SYH are the experimental sites at Yangling, Changwu, Jingyang, and Shiyanghe, respectively.
[b] *Sim.* and *Obs.* are simulation and observation, respectively.
[c] ARE is absolute relative error.

in using the observation method. Thus, harvest date was usually treated as the maturity date instead. The AREs of grain yield varied from almost 0–6.8%, but biomass errors were higher than yield. Generally, the CERES-Maize model performed well in our study areas and was considered acceptable for simulating local maize growth and yield.

3.2. Dynamic maize yield forecast within a given growing season

With the incorporation of newly measured weather data into the weather data on each day of a given growing season, maize yields were dynamically forecasted in 2010 (Fig. 4a) and 2011 (Fig. 4b) at Changwu. The AREs between predicted and actual final yields were calculated to assess forecast accuracy (with a time interval of 5 d in the figure for the sake of clarity). In general, the actual two-year yields were covered by the range of forecasted yields across the growing seasons. The distribution of forecasted yields was wide during early growth but converged closer to the actual yield after tasseling. For example, on 30, 60, and 90 DAP (days after planting), forecasted yield ranged from 3,531–14,461, 3,413–14,828 and 961–13,210 kg ha^{-1}, respectively. After tasseling, on 100 and 130 DAP, the forecasted yield ranges were 4933–10,826 and 8484–10,565 kg ha^{-1}. AREs of daily forecasted yields in the two growing season were small at the start of the growing season (less than 15%), but increased with time to the maximum at the tasseling stage (up to 35%). Then, AREs decreased rapidly after tasseling and remained relatively stable in the following days of the growing season (less than 8%). Generally, MAREs of the two growing seasons were 11.7% and 7.3%, respectively.

Using the weather data fusion method, actual weather data were incorporated into the historical weather series, which could produce extreme weather conditions in the middle of the growing season. In the early and late stages of the growing season, historical and actual weather data comprised the largest part of the generated weather series, respectively. Thus, the weather data series possessed general features that conformed to local weather conditions. However, in the middle of the growing season, maize developed quickly and was sensitive to weather conditions. Therefore, uncertainties arising from the weather data fusion could increase the uncertainties in the forecasted maize yields. Tasseling date was generally accepted as the transition between vegetative and reproductive growth stages. The maize plant canopy was almost steady at this stage. The maximum radiation interception ability and amount of nutrient mobilization by maize plants

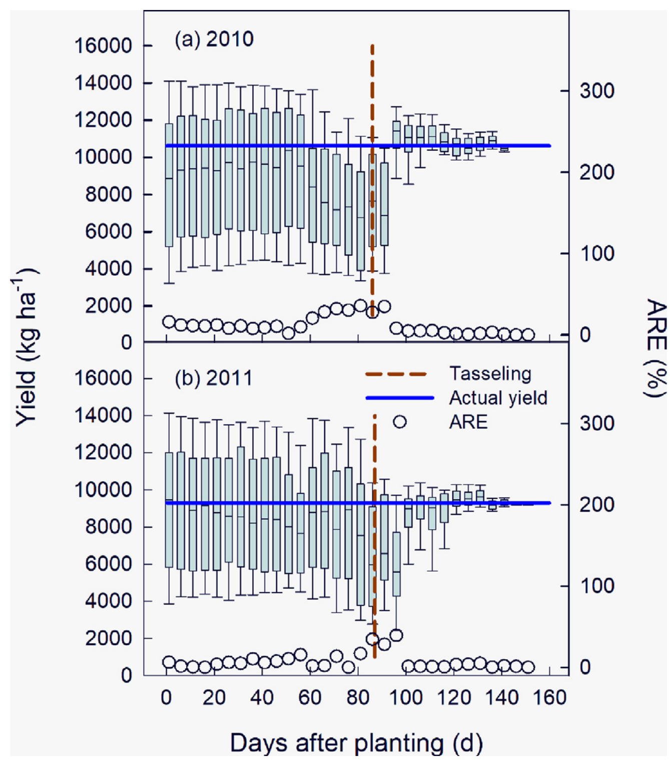

Fig. 4. Dynamics of forecast yields of spring maize based on weather data fusion and the CERES-Maize model in 2010 (a) and 2011 (b) at Changwu, Shannxi Province, China. Box plots show the forecasted yields at five-day intervals from planting to maturity. The edges of the boxes represent the 75th and 25th percentiles, while the whiskers are the 90th and 10th percentiles. The medians are shown as horizontal lines within the boxes. Open circles show the absolute relative error (ARE, %) of forecasted yields on each day. The horizontal solid line is the observed actual final yield. The vertical dashed line indicates the tasseling stage.

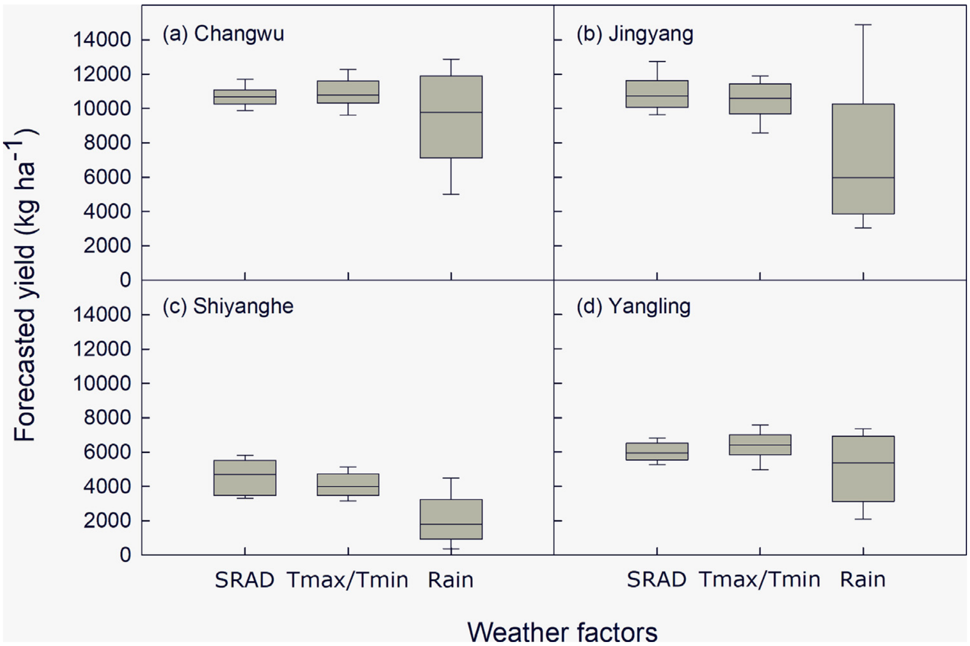

Fig. 5. Simulated maize yields for 50 years (1968–2017) with variations in three different weather variables (*SRAD, Tmax/Tmin*, and *Rain*) at Changwu (a), Jingyang (b), Shiyanghe (c), and Yangling (d). When simulating maize yields with variation in a given weather factor, the other weather factors were replaced by multi-year mean values on the same dates. *Tmax/Tmin* were considered as one factor and replaced by their individual means simultaneously. The edges of the boxes represent 75th and 25th percentiles, and the whiskers are 90th and 10th percentiles. The medians are the horizontal lines within the boxes.

had almost been determined at this stage. Thus, both the ranges and AREs of forecasted yields converged rapidly after tasseling.

3.3. Sensitivities of simulated maize yield to different weather variables

Three types of simulated maize grain yields over 50 years (1968–2017) were obtained from the CERES-Maize model running the three types of weather series generated in Changwu (Fig. 5). Generally, the simulated yields reflected the variation in weather factors. The distribution of maize yields under actual historic rainfall was much more dispersed than those under actual radiation and temperature. Compared with rainfall, simulated maize yields were relatively high and less variable under variable solar radiation and temperature. Similar results also occurred at the other three sites, indicating that rainfall was the most determinant factor for maize yield in the study areas. It should be noted that simulated maize yields were extremely low at Shiyanghe under all three weather factors across years (Fig. 5c). Maize production at this site was strongly dependent on irrigation due to its extreme arid weather, which was why predetermined irrigation was set at the maize tasseling stage in the CERES-Maize model before irrigation scheduling.

The median values of forecasted yields in Changwu followed a clear declining trend from 50–70 DAP in 2010 (Fig. 4a) and 20–35 and 70–85 DAP in 2011 (Fig. 4b). In 2011 at Changwu, the forecasted yields declined from 0–8, 18–26, and 29–54 DAP and increased immediately after the rains at 8, 26, and 54 DAP (Fig. 6). This kind of relationship demonstrated that the current yield forecasting method, based on weather data fusion and the CERES-Maize model, reflects the influence of real-time rainfall dates and amounts. Combined with the sensitivity of maize yield to the different weather variables above, the yield forecast algorithm could be used for maize irrigation scheduling.

3.4. Dynamic within-season irrigation scheduling program

3.4.1. Evaluation of the new irrigation scheduling program with different IT(DD, ID)

The influence of irrigation date and depth on grain yield and irrigation scheduling were evaluated with four different IT(*DD, ID*) functions at Changwu in 2011 (Fig. 7). In general, the forecasted maize yields responded properly to irrigation date and depth. Different dynamic irrigation suggestions could be automatically provided during

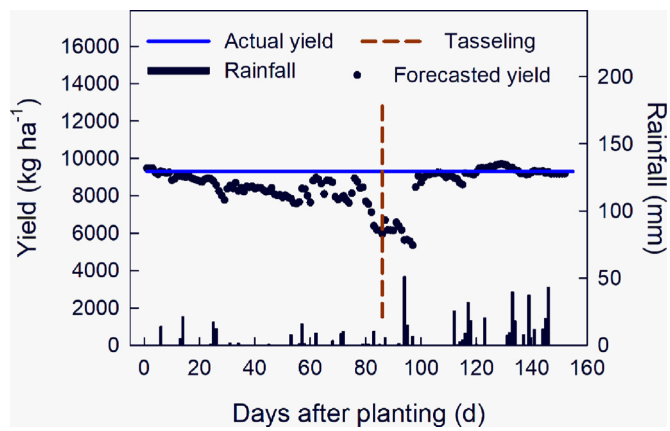

Fig. 6. Dynamics of forecasted yields of spring maize and rainfall during the 2011 growing season at Changwu (rainfed), Shaanxi Province. Vertical bars are rainfall. The horizontal solid line is actual maize yield and the vertical dotted line indicates the tasseling stage of spring maize.

the growing season based on the four different threshold functions of IT(*DD, ID*), where *DD* is the threshold of accumulative declining days of yield and *ID* is irrigation depth per event, e.g., IT(10 d, 40 mm) (Fig. 7a), IT(10 d, 80 mm) (Fig. 7b), IT(15 d, 40 mm) (Fig. 7c), and IT(15 d, 80 mm) (Fig. 7d). Irrigation events scheduled by the new algorithm all occurred in the early phase of the 2011 growing season (DAP < 40) at Changwu, which means that actual rainfall in this period was less than normal historical years and forecasted yields declined (Fig. 6). Irrigation date and amount affected final maize yield. Although total irrigation depths were all 80 mm, the simulated yields were 9,245 kg ha^{-1} for two irrigations of 40 mm (Fig. 7a), 10,076 kg ha^{-1} for two irrigations of 40 mm at a later date (Fig. 7c), and 10,954 kg ha^{-1} for one irrigation of 80 mm (Fig. 7d). The simulated results suggest that multiple lower-depth irrigation irrigations may not improve final maize yield. When irrigation depth reached 160 mm early in a given growing season, the forecasted yields reached about 13,000 kg ha^{-1} and maintained a high level after 30 DAP (Fig. 7b), indicating that water was the main limiting factor for maize yield in Changwu. The irrigation threshold function of IT(*DD, ID*) can be set by users, according to the availability of local water resources and yield expectations. Generally,

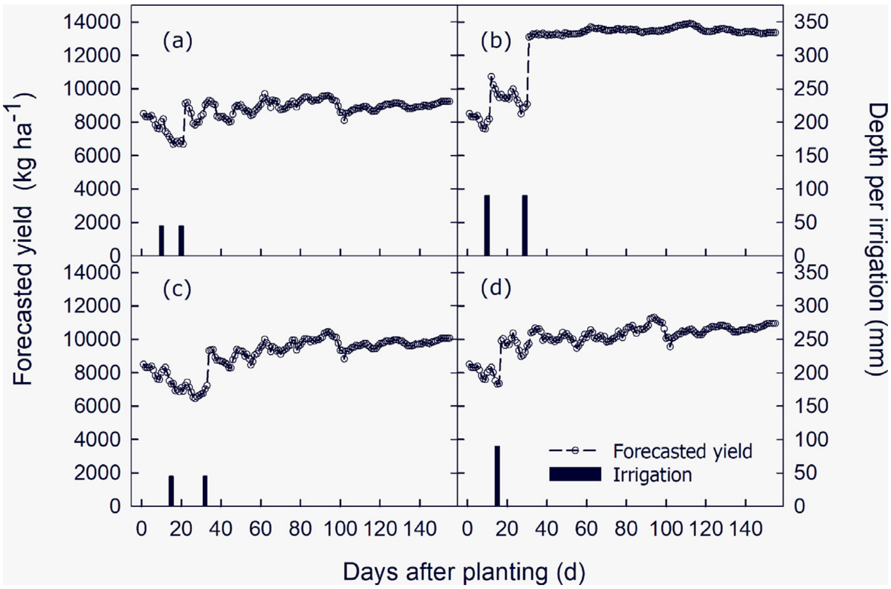

Fig. 7. Prediction of spring maize yield (open circles) with the dynamic within-season irrigation scheduling program in 2011 at Changwu, Shaanxi Province Irrigation events were scheduled based on four decision thresholds of IT(*DD, ID*), as a functions of cumulative declining days of simulated yields (*DD*) and irrigation depth per event (*ID*, black vertical bars), e.g. IT(10 d, 40 mm) (a), IT(10 d, 80 mm) (b), IT(15 d, 40 mm) (c), and IT(15 d, 80 mm) (d).

the new irrigation scheduling program developed in this study provides an automatic tool for improving water management in maize production.

3.4.2. Comparison among automatically scheduled and actual irrigations

The new dynamic within-season irrigation scheduling program and the automatic irrigation option in DSSAT were used to generate irrigation strategies based on the three irrigated maize experiments in this study. These irrigation strategies were then compared with local irrigation practices for simulated grain yield, irrigation times, total irrigation depth, and IUE (Table 3). Compared with local irrigation practices, IUEs improved with the new irrigation scheduling program and the DSSAT automatic irrigation option. However, there were remarkable differences in IUE and total irrigation amount between the different irrigation decision methods. The DSSAT automatic irrigation option had the most irrigations scheduled at every site, since soil water moisture was used as the irrigation determination variable. To maintain soil water content at a fixed threshold, frequent irrigations were applied with low depth per irrigation (35–45 mm). Hence, simulated yields with this option were higher than other irrigation strategies, since water stress was nearly curbed during the whole growing season.

Compared with the other irrigation strategies, the new dynamic irrigation scheduling program had fewer irrigations and consumed less water. The IUE also improved in dry years. However, the new program seemed inefficient when there was heavy rainfall. For example, the 2014 growing season at Yangling had a total rainfall of 381 mm, most of which was concentrated in August or during grain filling (Fig. 8). The rainfall matched the maize water requirements but caused low air temperatures, which reduced final maize yield. The results demonstrate that the new automatic irrigation scheduling program could be used for maize irrigation management in arid and semiarid areas, where water supply is usually limited during the maize growing season.

Table 3
Comparisons among the irrigation strategies based on local farmer experiences (identified as actual), the automatic irrigation option in DSSAT (identified as DSSAT auto-option), and the new dynamic within-season irrigation scheduling program (identified as new program) at Jingyang (JY), Yangling (YL), and Shiyanghe (SYH).

Site	Year	Rainfall (mm)	Irrigation scheduling					Simulated yield	IUE [a]
			Method	Depth per event (mm)	Determination factor	Irrigation times	Total amount (mm)	(kg ha^{-1})	(kg ha^{-1} mm^{-1})
JY	2015	218	Actual	90	Local experience	3	270	11326	41.9
			DSSAT auto-option	–	Soil moisture	6	280	12077	43.1
			New program [b]	90	Forecasted yields	3	270	11274	41.8
				45		4	180	9929	55.2
YL	2014	381	Actual	80	Local experience	2	160	6150	38.4
			DSSAT auto-option	–	Soil moisture	2	119	6153	51.7
			New program	80	Forecasted yields	2	160	6148	38.4
				40		3	120	6149	51.2
	2015	271	Actual	80	Local experience	2	160	7069	44.2
			DSSAT auto- option	–	Soil moisture	3	130	7018	54.0
			New program	80	Forecasted yields	1	80	7159	89.5
				40		1	40	6245	156.1
SYH	2015	151	Actual	123 + 103 + 113 + 41 + 62	Local experience	5	442	8747	19.8
			DSSAT auto- option	–	Soil moisture	9	387	8963	23.2
			New program	90 + (110) [c]	Forecasted yields	2 + 1	290	8420	29.0
				45 + (110)		3 + 1	245	7845	32.0

[a] IUE is irrigation use efficiency, as defined in Equation 2.

[b] In the new dynamic within-season scheduling program, an irrigation event of IT(*DD, ID*) was defined as a function of *DD* (cumulative declining days of maize yield) and *ID* (irrigation depth per event). The value of *DD* was set to 10 days and the value of *ID* had two levels of depth that applied by local farmers and half the value.

[c] SYH, or Shiyanghe had an original irrigation depth of 110 mm at 96 DAP. Annual mean rainfall at Shiyanghe was only 162 mm, which did not satisfy water requirement of maize. Therefore, the new program could not capture a decreasing trend of forecasted yields asked for maize irrigation scheduling. Thus, predetermined irrigation of 110 mm (as shown the parentheses) according to local experience was added to the model to ensure that the new program worked.

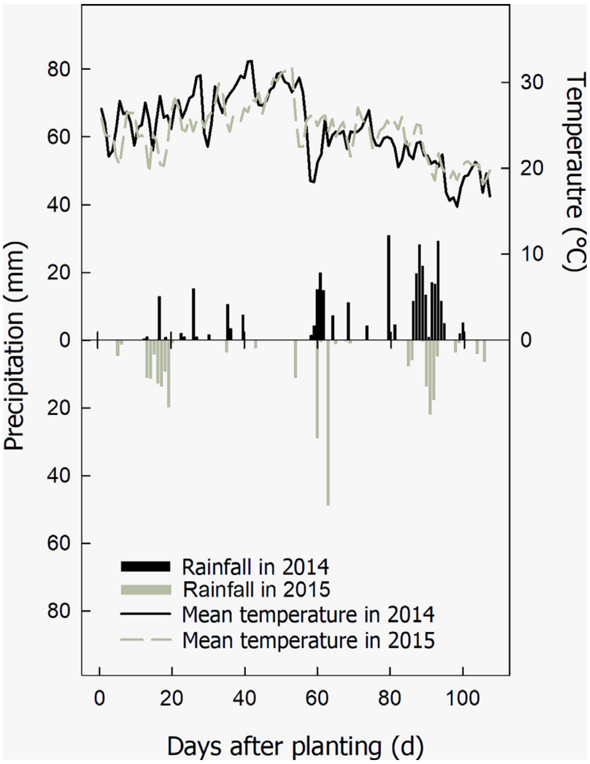

Fig. 8. Rainfall and mean air temperature during the maize growing season in 2014 and 2015 at Yangling, Shannxi Province. Vertical bars are rainfall. Black solid and pink dashed lines are mean temperatures in the two growing seasons, respectively.

4. Discussion

4.1. Maize yield forecast based on weather data fusion and crop model

Forecasting crop growth with crop models usually requires a complete weather data series that covers the whole growing season of a given crop. Apart from readily available weather data before a given date, unknown weather data for a growing season can be represented by seasonal weather forecasts (e.g., weather generators, coupled ocean-atmosphere climate models) or historical weather records. Crop yield forecasts based on historical weather records tend to be more accurate than seasonal forecasted weather data (Marletto et al., 2007; Prakash et al., 2019). This study used weather ensembles by incorporating daily measured weather data and historical weather data in the CERES-Maize model in DSSAT to dynamically predict within-season maize yields at four sites in Northwest China. High accuracy of yield forecasts occurred for almost 50 days before maturity for spring maize at Changwu (Fig. 4). The results demonstrated that the precision of yield prediction was acceptable by only using historical weather records in the maize model, which avoided errors and uncertainties in downscaling and other processes of climate models (Goel and Dash, 2007).

In the process of daily yield forecasting, the uncertainty and errors of forecasted grain yields did not initially decrease as the proportion of actual weather data increased in the weather data series. Yield uncertainty at a given date mainly resulted from weather variation during the remaining time of the growing season. The forecast accuracy should have improved as the number of days with unknown weather decreased during the growing season. However, the results identified a predictability threshold of developmental stage for maize yield. When maize reached tasseling, the forecasted yields began to converge with actual yields, and was similar to the anthesis date for wheat yield forecasts by Lawless and Semenov (2005). The formation of maize grain yield can be described as a source–sink relationship that is mainly limited by source capacity or sink demand for assimilates during grain filling. When maize reaches tasseling, it enters reproductive growth and has a fully developed canopy with maximum radiation interception ability. Thus, yield uncertainty from variable weather conditions was greatly reduced. DeJonge et al. (2011) pointed out that the CERES-Maize model could simulate maize anthesis date accurately in semiarid environment, which was consistent with this study and important for maize grain yield simulation.

In this study, we used historical weather data from 1968 to 2017 as possible weather scenarios to forecast maize yield. The large uncertainty in forecasted yields resulted from variable rainfall patterns in the given growing seasons. Bannayan and Hoogenboom (2008) reported that the selection of analog years from historical meteorological data might reduce the uncertainty in forecasted yields. Wang et al. (2017) used different numbers of years of historical weather records to represent the unknown weather data in the growing season to forecast cotton yield. They identified that the forecasted yields predicted by the most recent ten years of weather data had the highest accuracy. This finding is important due to the limited number of years with historical weather data. However, their conclusions are site-specific and may vary under different climate conditions. In our study, we wanted to demonstrate the potential of the new program in irrigation scheduling with insight into quantifying the real-time influence of irrigation on seasonal yields., Weather records with different numbers of years could be tested in further work. More research is needed to assimilate information from multiple remote sensing sources (Mokhtari et al., 2018; Pagani et al., 2018), and effective seasonal weather predictions (Brown et al., 2018; Ogutu et al., 2018) need to be incorporated into crop models to improve the regional predictability of maize yields.

4.2. New dynamic within-season irrigation scheduling program

4.2.1. Comparisons among the new and common model-based irrigation scheduling

Global climate changes might make irrigation a more attractive option because farmers have to take into consideration of economic benefits and field production capacity into agronomic management practices (Xu et al., 2019). Therefore, highest economic returns, available irrigation water, possible weather in the coming days of the growing season should be accepted in irrigation scheduling. Our irrigation scheduling algorithm provides users with a tool to quantify the influences of different irrigation dates and amounts on seasonal maize grain yield. Field managers could decide whether irrigate according to simulations based on their yield expectations and available irrigation water. Compared with the new dynamic irrigation scheduling program, common irrigation strategies based on crop model simulations are usually static and 'one size fits all', as irrigation schedules based on optimizing limited field experiments are applied to all years (Linker and Kisekka, 2017; Ma et al., 2017). Irrigation strategies scheduled in this way may become ineffective or even invalid when weather conditions change.

Furthermore, the main obstacle in common model-based method is the need for high simulation accuracy of some output variables (such as soil water content) for irrigation scheduling. Two reference ET calculation options were offered to users in DSSAT v4.6: (1) Priestley–Taylor (PT) which only uses four weather variables—*Tmin, Tmax, Rain*, and Solar radiation Priestley and Taylor, 1972), and (2) FAO-56 Penman–Monteith method (PM-FAO56) which also include wind speed and air humidity (Allen et al., 1998). Sau et al. (2004) evaluated four ET estimation methods and their effects on ET, soil water content, and crop biomass accumulation under rainfed conditions in southwest Spain. The author reported that the PT and PM-FAO56 methods simulated crop growth well but tended to overpredict and underpredict ET, respectively. Anothai et al. (2013) evaluated the two ET options in the DSSAT-

CERES-Maize model under different irrigation strategies, reporting the simulation errors in daily and seasonal ET were less than 12%. The authors confirmed the potential of using both ET approaches for agricultural water management under water-limited conditions. In addition, we used the tendency of daily forecast yields rather than direct model outputs to schedule irrigations in this study. Therefore, the model only needed to correctly show consistent real-time responses to water factors rather than had high simulation accuracy for all processes in the model. With the fusion of newly measured daily weather data and historical weather series, maize grain yield could be forecasted day-by-day over the whole growing season. Whether to irrigate or not in our new program was determined by the trends of dynamically forecasted yields which responding to real-time weather rather than following a fixed irrigation schedule for all situations. The simulated IUEs of irrigations scheduled by the new algorithm at the four sites were improved, relative to strategies scheduled by local farmers' experience or the DSSAT automatic irrigation options. However, three key variables in the DSSAT automatic irrigation option were set as default values. Different combinations of these irrigation variables might result in different irrigation strategies and IUEs.

Byun and Wilhite (1999) used frequency, severity and duration the three variables to assess levels of drought. Irrigations are mainly used to resist the negative effects of heavy drought on agriculture and should be avoided when drought level is slight to save cost. This new irrigation scheduling program provided trends of within-season yield forecasts and irrigation suggestions by taking into account real weather conditions in a given growing season. Grain yield was usually the main target for agricultural management. Our new irrigation scheduling program based on yield forecasting was thus more purposeful. When the declining trend of forecasted yields occurred first, it meant less rainfall than historical records, but did not necessarily mean a very serious water stress. However, if the declining trend lasted for a longer time, some serious drought must have happened and irrigation should be applied immediately. In this new program, we defined the irrigation threshold IT(DD, IT) as a function of DD and ID, where DD (d) is the threshold number accumulated days of decreasing forecasted yields which describing user's tolerance to the duration of yield decreasing, and ID (mm) is the irrigation depth per event. The values of these two variables could be set by users before running this program. Irrigation called by the declining yields would not be permitted in the program when the duration of yield reduction was less than expectation. Users are allowed to set a small value of DD if irrigation must start 2–3 days in advance to avoid crop water stress of part of the field. Furthermore, yield expectation can be added as a variable in the new program. Irrigation would be applied if the forecasted yields are less than the target yields.

4.2.2. Deficiency and improvement of the new irrigation scheduling program

It should be noted that irrigations scheduled by model simulations are imperfect due to model structure simplification of crop biophysical processes and uncertainty in model parameters Kisekka et al., 2017. Irrigation strategies scheduled by our new algorithm were only used in the CERES-Maize model to simulate maize growth and yields without actual field application. Further work should take actual field conditions into consideration. However, despite the above disadvantages, crop models are still useful tools for considering the interactions of weather, soil, management practices, and crop cultivars. The new dynamic within-season irrigation scheduling program was developed on the hypothesis that the declining trend of forecasted yields mainly results from a reduction in rainfall compared with normal years. The results demonstrated that this assumption worked in most of the investigated years and sites. However, the new program would be ineffective in two cases: (1) agricultural oasis with extreme drought conditions and (2) heavy rainfall during the growing season that would satisfy the maize water requirement.

Mean annual rainfall was only 162 mm at Shiyanghe in Gansu Province, while mean annual pan evaporation was about 2000 mm. Simulated maize still had grain yield with 162 mm precipitation at this site, mainly due to water that had been stored in the soil profile at the start of the growing season, which ensured seedling emergence; and the simulation error of DSSAT under high water stress conditions. Ben Nouna et al. (2000) pointed out that the CERES-Maize model underestimates leaf area index, aboveground biomass and grain yield under mild soil water shortage. In this study, the DSSAT-CERES-Maize model had been validated according to experimental observations (irrigated) before been used in irrigation scheduling, the simulation error of anthesis date, harvest date, grain yield and aboveground biomass were acceptable. Furthermore, we used the trends of daily forecasted maize yields rather than single model outputs to guide irrigation. It was supposed that the application of trends of daily forecasted yields could reduce the simulation error caused by model deficiency under water stress. Although daily forecasted rainfed maize yields with 50-year historical weather series were almost all less than 2000 kg ha^{-1}, the program failed to capture a declining trend of daily forecasted yields or provide irrigation suggestions due to the lack of variation in yield predictions in such dry conditions, which was a prerequisite for irrigation scheduling in the new program. To overcome this shortcoming, predetermined irrigation to 110 mm was set 96 DAP or the time of local maize tasseling according to local field management. With this additional irrigation, variations in forecasted maize yields increased dramatically with the 50-year weather data series. In contrast, Yangling had 384 mm rainfall during the 2014 growing season, most of which occurred in August or during grain filling (Fig. 8). The maize water requirement was well satisfied, but low air temperatures caused by continuous rainy days reduced final grain yield. The declining trend in forecasted yields was treated as a signal for water application in the new program, although the reduction in forecasted maize yields could have been caused by other non-water stresses. Liu et al. (2017) developed an optimal irrigation schedule for cotton by using the water stress indices computed by DSSAT embedded in the RZWQM, which could be adopted in the further development of our program. Besides, rainfall following irrigation may result in unnecessary water application (Cao et al., 2019). Thus, incorporating possible short-term weather forecasts, especially rainfall, into irrigation scheduling is a powerful tool for reducing irrigation water (Cai et al., 2011; Linker and Sylaios, 2016). In next step, we want to add short-term weather forecast data in the generated seasonal weather series in the format of "real-time measurements + short-term prediction + historical records". Further studies are needed to include maize water requirements at different growing stages and imminent rainfall forecasts in our new dynamic within-season irrigation scheduling program.

5. Conclusion

A new within-season irrigation scheduling method was established based on trends in daily yield predictions. By incorporating daily new measurements with local historical weather data, yields forecasted by the DSSAT-CERES-Maize model responded to actual weather conditions that had happened before forecast date. The uncertainty in forecasted maize yields was large in the early growing season but converged soon after the tasseling stage. High accuracy of maize yield forecasts occurred nearly 35 days before maturity. Based on the analysis of sensitive weather factor to maize yield in our research areas, variations of seasonal accumulative precipitation caused the largest uncertainty in simulated maize yields at the four sites in 1968–2017. In the new irrigation scheduling method, reduction trends caused by more serious water stress in daily forecasted yields were treated as indicators calling for irrigation events. Compared with the irrigation strategies scheduled by farmer experiences or the automatic irrigation option in DSSAT, our new dynamic within-season irrigation scheduling program suggested more efficient irrigation strategies in most cases, except at Yangling in 2014 due to heavy rainfall during grain filling. This new irrigation scheduling program assumed that the reduction of daily forecasted yield was caused by lessened accumulative precipitation but did not consider water requirements at different maize growth stages. Future research should consider crop water status and short-term daily weather forecasts to improve the accuracy of the new irrigation scheduling program.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2020.107928.

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